Gov 50: 8. Summarizing Data

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Roadmap

1. Descriptive Statistics
2. Missing data
3. Proportion tables

1/ Descriptive Statistics

Lots of data

```r
library(tidyverse)
library(gapminder)
gapminder
```

```
## # A tibble: 1,704 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ... with 1,694 more rows
```

Lots and lots of data

```r
head(gapminder$gdpPercap, n = 200)
```

```
##   [1]   779   821   853   836   740   786   978   852   649
##  [10]   635   727   975  1601  1942  2313  2760  3313  3533
##  [19]  3631  3739  2497  3193  4604  5937  2449  3014  2551
##  [28]  3247  4183  4910  5745  5681  5023  4797  5288  6223
##  [37]  3521  3828  4269  5523  5473  3009  2757  2430  2628
##  [46]  2277  2773  4797  5911  6857  7133  8053  9443 10079
##  [55]  8998  9140  9308 10967  8798 12779 10040 10950 12217
##  [64] 14526 16789 18334 19477 21889 23425 26998 30688 34435
##  [73]  6137  8843 10751 12835 16662 19749 21597 23688 27042
##  [82] 29096 32418 36126  9867 11636 12753 14805 18269 19340
##  [91] 19211 18524 19036 20292 23404 29796   684   662   686
## [100]   721   630   660   677   752   838   973  1136  1391
## [109]  8343  9715 10991 13149 16672 19118 20980 22526 25576
## [118] 27561 30486 33693  1063   960   949  1036  1086  1029
## [127]  1278  1226  1191  1233  1373  1441  2677  2128  2181
## [136]  2587  2980  3548  3157  2754  2962  3326  3413  3822
## [145]   974  1354  1710  2172  2860  3528  4127  4314  2547
## [154]  4766  6019  7446   851   918   984  1215  2264  3215
## [163]  4551  6206  7954  8647 11004 12570  2109  2487  3337
## [172]  3430  4986  6660  7031  7807  6950  7958  8131  9066
```

How to summarize data

- How should we summarize the wages data? Many possibilities!
  - Up to now: focus on **averages** or means of variables.
- Two salient features of a variable that we want to know:
  - **Central tendency**: where is the middle/typical/average value.
  - **Spread** around the center: are all values to the center or spread out?

Center of the data

- "Center" of the data: typical/average value.
- **Mean**: sum of the values divided by the number of observations

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

- **Median**:

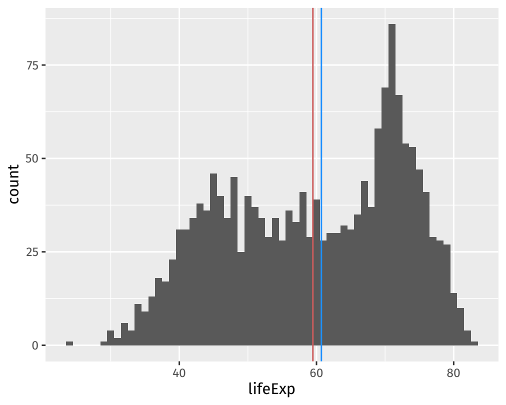
$$\text{median} = \begin{cases} \text{middle value} & \text{if number of entries is odd} \\ \frac{\text{sum of two middle values}}{2} & \text{if number of entries is even} \end{cases}$$

- In **R**: `mean()` and `median()`.

Mean vs median

- Median more robust to **outliers**:
  - Example 1: data = $\{0, 1, 2, 3, 5\}$. Mean? Median?
  - Example 2: data = $\{0, 1, 2, 3, 100\}$. Mean? Median?
- What does Mark Zuckerberg do to the mean vs median income?

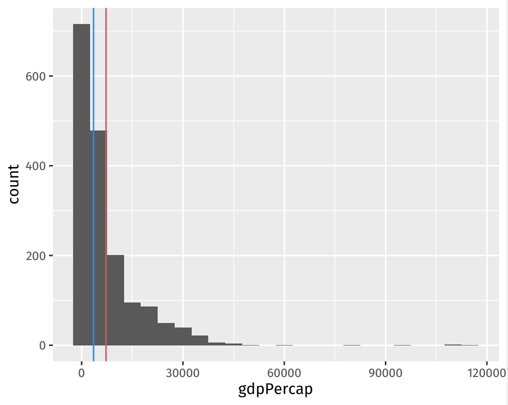
```r
ggplot(gapminder, aes(x = lifeExp)) +
  geom_histogram(binwidth = 1) +
  geom_vline(aes(xintercept = mean(lifeExp)), color = "indianred") +
  geom_vline(aes(xintercept = median(lifeExp)), color = "dodgerblue")
```




```r
summary(gapminder$lifeExp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    23.6    48.2    60.7    59.5    70.8    82.6
```

```r
ggplot(gapminder, aes(x = gdpPercap)) +
  geom_histogram(binwidth = 5000) +
  geom_vline(aes(xintercept = mean(gdpPercap)), color = "indianred") +
  geom_vline(aes(xintercept = median(gdpPercap)), color = "dodgerblue")
```

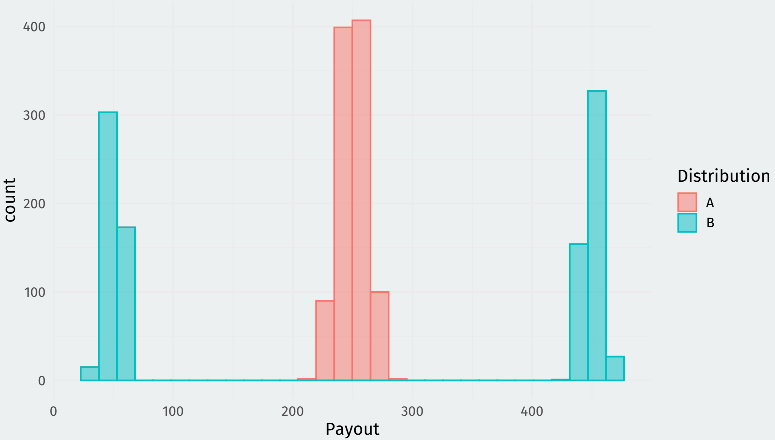



```r
summary(gapminder$gdpPercap)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##      241     1202     3532     7215     9325   113523
```

Which distribution would you prefer?

Lottery where we randomly draw one value from A or B:



They have the same mean, so why do we care about the difference? **Spread!!**

Spread of the data

- Are the values of the variable close to the center?
- **Range**: $[\min(X),\ \max(X)]$
- **Quantile** (quartile, percentile, etc): divide data into equal sized groups.
  - 25th percentile = lower quartile (25% of the data below this value)
  - 50th percentile = median (50% of the data below this value)
  - 75th percentile = upper quartile (75% of the data below this value)
- **Interquartile range** (IQR): a measure of variability
  - How spread out is the middle half of the data?
  - Is most of the data really close to the median or are the values spread out?
- **R** function: `range()`, `summary()`, `IQR()`

Standard deviation

- **Standard deviation**: On average, how far away are data points from the mean?

$$\text{standard deviation} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

- Steps:
  1. Subtract each data point by the mean.
  2. Square each resulting difference.
  3. Take the sum of these values
  4. Divide by $n - 1$ (or n, doesn't matter much)
  5. Take the square root.
- **Variance** = standard deviation^2
- Why not just take the average deviations from mean without squaring?

2/ Missing data

Missing data

- **Nonresponse**: respondent can't or won't answer question.
  - Sensitive questions ⇝ **social desirability bias**
  - Some countries lack official statistics like unemployment.
  - Leads to missing data.
- Missing data in R: a special value NA
- Have already seen how to use `na.rm = TRUE`

CCES data

```r
library(gov50data)
cces_2020
```

```
## # A tibble: 51,551 x 6
##    gender race  educ                 pid3    turno~1 pres_~2
##    <fct>  <fct> <fct>                <fct>     <dbl> <fct>
##  1 Male   White 2-year               Republ~       1 Donald~
##  2 Female White Post-grad            Democr~      NA <NA>
##  3 Female White 4-year               Indepe~       1 Joe Bi~
##  4 Female White 4-year               Democr~       1 Joe Bi~
##  5 Male   White 4-year               Indepe~       1 Other
##  6 Male   White Some college         Republ~       1 Donald~
##  7 Male   Black Some college         Not su~      NA <NA>
##  8 Female White Some college         Indepe~       1 Donald~
##  9 Female White High school graduate Republ~       1 Donald~
## 10 Female White 4-year               Democr~       1 Joe Bi~
## # ... with 51,541 more rows, and abbreviated variable names
## #   1: turnout_self, 2: pres_vote
```

drop_na() to remove rows with missing values

```r
cces_2020 |>
  drop_na()
```

```
## # A tibble: 45,651 x 6
##    gender race  educ                 pid3    turno~1 pres_~2
##    <fct>  <fct> <fct>                <fct>     <dbl> <fct>
##  1 Male   White 2-year               Republ~       1 Donald~
##  2 Female White 4-year               Indepe~       1 Joe Bi~
##  3 Female White 4-year               Democr~       1 Joe Bi~
##  4 Male   White 4-year               Indepe~       1 Other
##  5 Male   White Some college         Republ~       1 Donald~
##  6 Female White Some college         Indepe~       1 Donald~
##  7 Female White High school graduate Republ~       1 Donald~
##  8 Female White 4-year               Democr~       1 Joe Bi~
##  9 Female White 4-year               Democr~       1 Joe Bi~
## 10 Female White 4-year               Democr~       1 Joe Bi~
## # ... with 45,641 more rows, and abbreviated variable names
## #   1: turnout_self, 2: pres_vote
```

Drop rows based on certain variables

```
cces_2020 |>
  dim_desc()
```

```
## [1] "[51,551 x 6]"
```

```
cces_2020 |>
  drop_na() |>
  dim_desc()
```

```
## [1] "[45,651 x 6]"
```

```
cces_2020 |>
  drop_na(turnout_self) |>
  dim_desc()
```

```
## [1] "[48,462 x 6]"
```

Available-case vs complete-case analysis

Available-case analysis: use the data you have for that variable:

```
cces_2020 |>
  summarize(mean(turnout_self, na.rm = TRUE)) |>
  pull()
```

```
## [1] 0.942
```

Complete-case analysis: only use units that have data on all variables

```
cces_2020 |>
  drop_na() |>
  summarize(mean(turnout_self)) |>
  pull()
```

```
## [1] 0.999
```

(also called **listwise deletion**)

`is.na()` to detect missingness

Trying to detect missingness with `==` doesn't work:

```
c(5, 6, NA, 0) == NA
```

```
## [1] NA NA NA NA
```

Use `is.na()` instead:

```
is.na(c(5, 6, NA, 0))
```

```
## [1] FALSE FALSE  TRUE FALSE
```

Can use `sum()` or `mean()` on this to get number/proportion missing:

```
sum(is.na(c(5, 6, NA, 0)))
```

```
## [1] 1
```

Nonresponse bias

Nonresponse can create bias if lower turnout ⇒ more non-response:

```
cces_2020 |>
  group_by(pid3) |>
  summarize(
    mean_turnout = mean(turnout_self, na.rm = TRUE),
    missing_turnout = mean(is.na(turnout_self))
  )
```

```
## # A tibble: 5 x 3
##   pid3        mean_turnout missing_turnout
##   <fct>              <dbl>           <dbl>
## 1 Democrat           0.963          0.0280
## 2 Republican         0.953          0.0403
## 3 Independent        0.924          0.0718
## 4 Other              0.957          0.0709
## 5 Not sure           0.630          0.431
```

3/ Proportion tables

Review of getting counts

First, let's review how to get counts:

```
cces_2020 |>
  group_by(pres_vote) |>
  summarize(n = n())
```

```
## # A tibble: 7 x 2
##   pres_vote                      n
##   <fct>                      <int>
## 1 Joe Biden (Democrat)       26188
## 2 Donald J. Trump (Republican) 17702
## 3 Other                       1458
## 4 I did not vote in this race    100
## 5 I did not vote                 13
## 6 Not sure                      190
## 7 <NA>                         5900
```

First attempt to create proportions

```r
cces_2020 |>
  group_by(pres_vote) |>
  summarize(prop = n() / sum(n()))
```

```
## # A tibble: 7 x 2
##   pres_vote                         prop
##   <fct>                            <dbl>
## 1 Joe Biden (Democrat)                 1
## 2 Donald J. Trump (Republican)         1
## 3 Other                                1
## 4 I did not vote in this race          1
## 5 I did not vote                       1
## 6 Not sure                             1
## 7 <NA>                                 1
```

Inside `summarize()` all operations are done within groups!

Mutate after summarizing

```
cces_2020 |>
  group_by(pres_vote) |>
  summarize(n = n()) |>
  mutate(prop = n / sum(n))
```

```
## # A tibble: 7 x 3
##   pres_vote                        n     prop
##   <fct>                        <int>    <dbl>
## 1 Joe Biden (Democrat)         26188 0.508
## 2 Donald J. Trump (Republican) 17702 0.343
## 3 Other                         1458 0.0283
## 4 I did not vote in this race    100 0.00194
## 5 I did not vote                  13 0.000252
## 6 Not sure                       190 0.00369
## 7 <NA>                          5900 0.114
```

Grouping is silently dropped after `summarize()`

Multiple grouping variables

What happens with multiple grouping variables

```
cces_2020 |>
  filter(pres_vote %in% c("Joe Biden (Democrat)",
                          "Donald J. Trump (Republican)")) |>
  group_by(pid3, pres_vote) |>
  summarize(n = n()) |>
  mutate(prop = n / sum(n))
```

```
## # A tibble: 10 x 4
## # Groups:   pid3 [5]
##    pid3        pres_vote                          n   prop
##    <fct>       <fct>                          <int>  <dbl>
##  1 Democrat    Joe Biden (Democrat)           17649 0.968
##  2 Democrat    Donald J. Trump (Republican)     581 0.0319
##  3 Republican  Joe Biden (Democrat)             856 0.0712
##  4 Republican  Donald J. Trump (Republican) 11164 0.929
##  5 Independent Joe Biden (Democrat)            6601 0.571
##  6 Independent Donald J. Trump (Republican)  4951 0.429
##  7 Other       Joe Biden (Democrat)             735 0.487
##  8 Other       Donald J. Trump (Republican)     774 0.513
##  9 Not sure    Joe Biden (Democrat)             347 0.599
## 10 Not sure    Donald J. Trump (Republican)     232 0.401
```

With multiple grouping variables, `summarize()` drops the last one.

Dropping all groups

If we want the proportion of all rows, need to drop all groups.

```
cces_2020 |>
  filter(pres_vote %in% c("Joe Biden (Democrat)",
                          "Donald J. Trump (Republican)")) |>
  group_by(pid3, pres_vote) |>
  summarize(n = n(), .groups = "drop") |>
  mutate(prop = n / sum(n))
```

```
## # A tibble: 10 x 4
##    pid3        pres_vote                        n    prop
##    <fct>       <fct>                        <int>   <dbl>
##  1 Democrat    Joe Biden (Democrat)         17649 0.402
##  2 Democrat    Donald J. Trump (Republican)   581 0.0132
##  3 Republican  Joe Biden (Democrat)           856 0.0195
##  4 Republican  Donald J. Trump (Republican) 11164 0.254
##  5 Independent Joe Biden (Democrat)          6601 0.150
##  6 Independent Donald J. Trump (Republican)  4951 0.113
##  7 Other       Joe Biden (Democrat)           735 0.0167
##  8 Other       Donald J. Trump (Republican)   774 0.0176
##  9 Not sure    Joe Biden (Democrat)           347 0.00791
## 10 Not sure    Donald J. Trump (Republican)   232 0.00529
```