Gov 50: 10. Survey Sampling

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Roadmap

1. Proportion tables

2. Measurement

1/ Proportion tables

CCES Data

```
library(gov50data)
cces_2020
```

```
## # A tibble: 51,551 x 6
##    gender race  educ                pid3  turnout_self pres_vote
##    <fct>  <fct> <fct>               <fct>        <dbl> <fct>
##  1 Male   White 2-year              Repu~            1 Donald J~
##  2 Female White Post-grad           Demo~           NA <NA>
##  3 Female White 4-year              Inde~            1 Joe Bide~
##  4 Female White 4-year              Demo~            1 Joe Bide~
##  5 Male   White 4-year              Inde~            1 Other
##  6 Male   White Some college         Repu~            1 Donald J~
##  7 Male   Black Some college         Not ~           NA <NA>
##  8 Female White Some college         Inde~            1 Donald J~
##  9 Female White High school gr~ Repu~            1 Donald J~
## 10 Female White 4-year              Demo~            1 Joe Bide~
## # i 51,541 more rows
```

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
```

Another approach

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

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

Doesn't work if you have filtered the data in any way during the pipe

Multiple grouping variables

What happens with multiple grouping variables

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

vote_by_party
```

```
## # A tibble: 10 x 3
## # Groups:   pid3 [5]
##    pid3        pres_vote   prop
##    <fct>       <chr>      <dbl>
##  1 Democrat    Biden     0.968
##  2 Democrat    Trump     0.0319
##  3 Republican  Biden     0.0712
##  4 Republican  Trump     0.929
##  5 Independent Biden     0.571
##  6 Independent Trump     0.429
##  7 Other       Biden     0.487
##  8 Other       Trump     0.513
##  9 Not sure    Biden     0.599
## 10 Not sure    Trump     0.401
```

```
## # A tibble: 10 x 3
## # Groups:   pid3 [5]
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##    <fct>       <chr>      <dbl>
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##  9 Not sure    Biden     0.599
## 10 Not sure    Trump     0.401
```
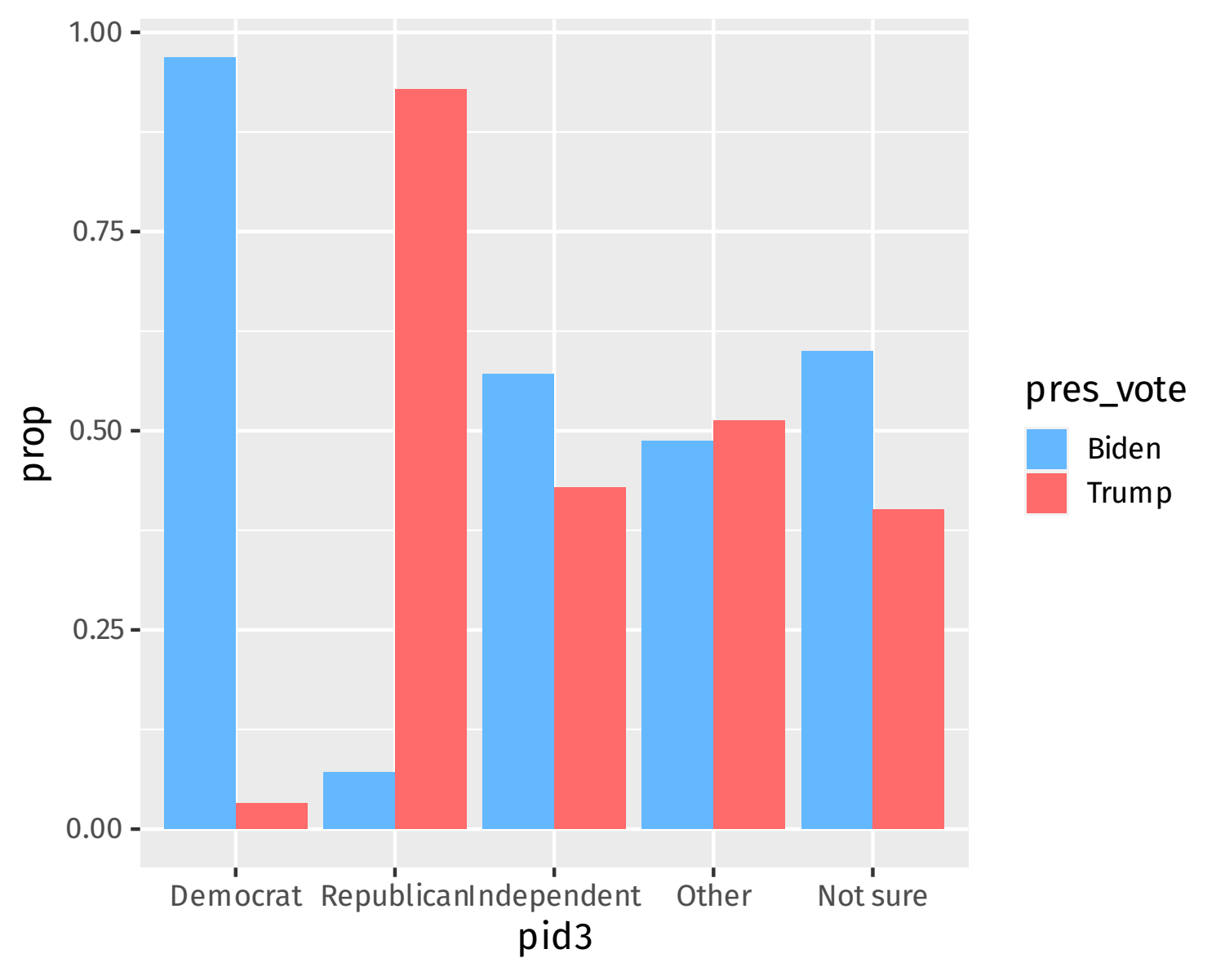

With multiple grouping variables, `summarize()` drops the last one.

Visualizing the cross-tab

We can visualize this using the `fill` aesthetic and `position="dodge"`:

```
ggplot(vote_by_party,
       aes(x = pid3, y = prop, fill = pres_vote)) +
  geom_col(position = "dodge") +
  scale_fill_manual(values = c(Biden = "steelblue1", Trump = "indianred1"))
```


1.00
0.75
0.50
0.25
0.00
prop
Democrat
Republican
Independent
Other
Not sure
pid3
pres_vote
Biden
Trump

Pivoting to create cross-tab

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

```
## # A tibble: 2 x 6
##   pres_vote Democrat Republican Independent Other `Not sure`
##   <chr>        <dbl>      <dbl>       <dbl> <dbl>      <dbl>
## 1 Biden       0.968      0.0712       0.571 0.487      0.599
## 2 Trump       0.0319     0.929        0.429 0.513      0.401
```

What if we want row proportions?

Switch the grouping variables to switch denominator:

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

```
## # A tibble: 2 x 6
## # Groups:   pres_vote [2]
##   pres_vote Democrat Republican Independent  Other
##   <chr>        <dbl>      <dbl>       <dbl>  <dbl>
## 1 Biden       0.674      0.0327       0.252 0.0281
## 2 Trump       0.0328     0.631        0.280 0.0437
## # i 1 more variable: `Not sure` <dbl>
```

Proportion of all observations

If we want the proportion of all rows, drop all groups

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

```
## # A tibble: 2 x 6
##   pres_vote Democrat Republican Independent  Other
##   <chr>        <dbl>      <dbl>       <dbl>  <dbl>
## 1 Biden       0.402      0.0195       0.150 0.0167
## 2 Trump       0.0132     0.254        0.113 0.0176
## # i 1 more variable: `Not sure` <dbl>
```

2/ Measurement

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    - Does outgroup contact influence views on immigration?

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- Theories are made up of **concepts**:
    - Minimum wage, level of employment, outgroup contact, views on immigration.
    - We took these for granted when talking about causality.
- Need **operational definition** to concretely measure these concepts

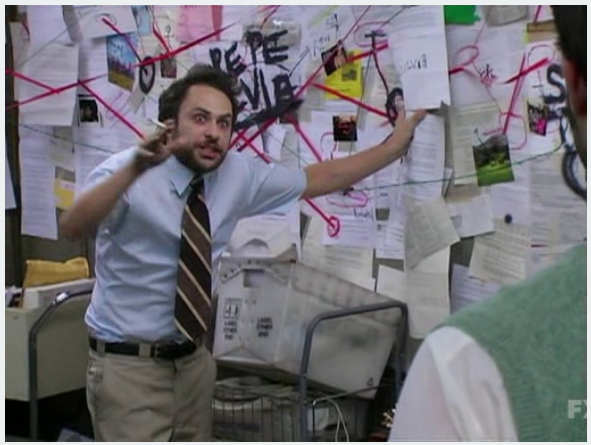
Concepts vary in how observable they are

Kinds of measurement arranged by how direct we can measure them:

Observable in the world

- Minimum wage laws

Observable by survey



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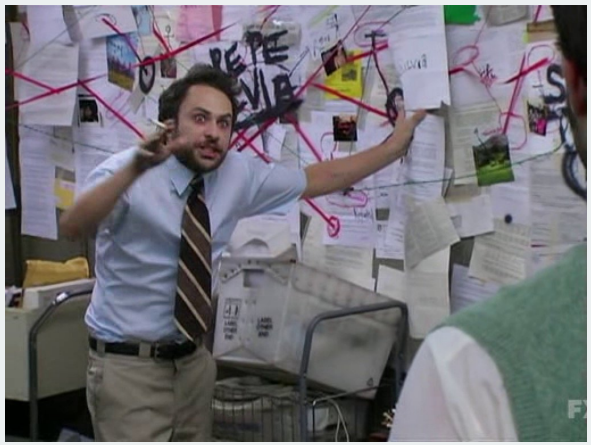

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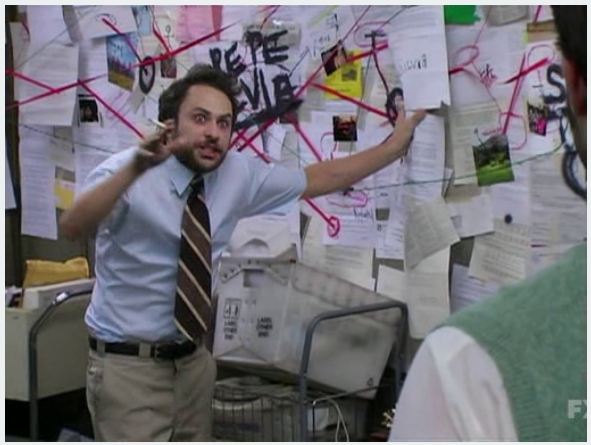

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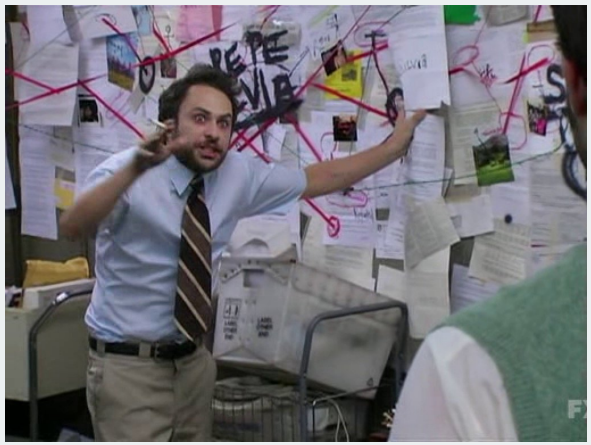

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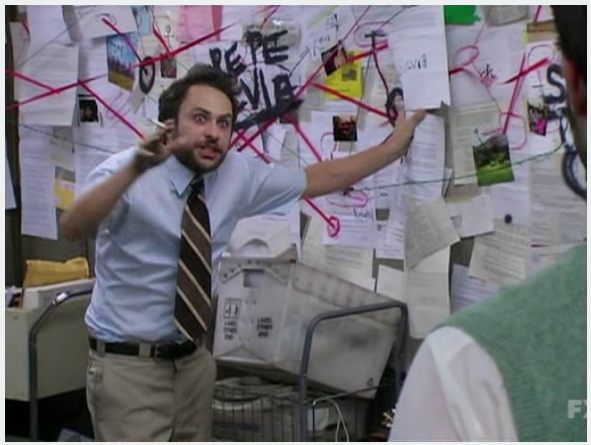

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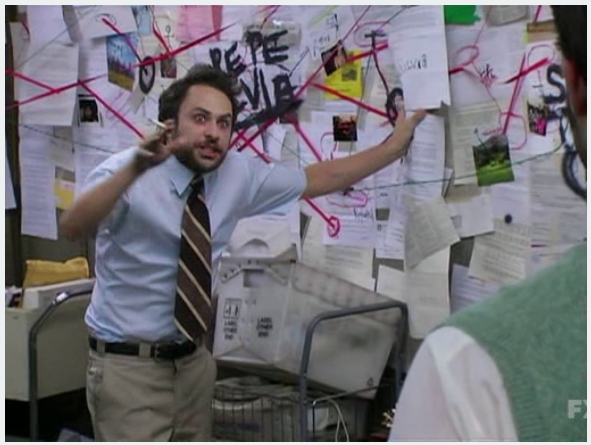

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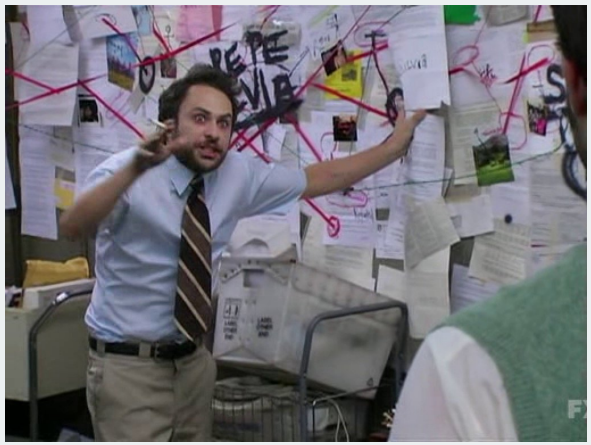

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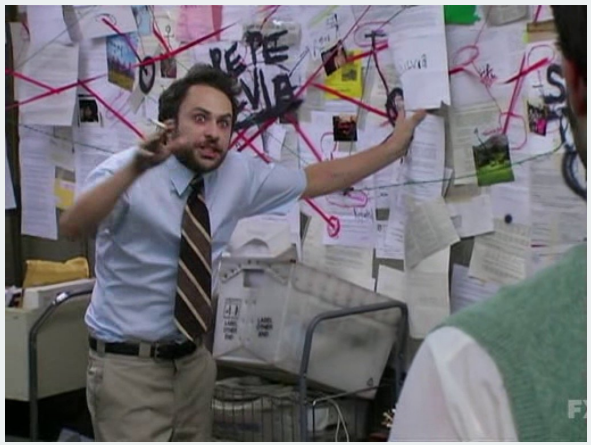

Not directly observable

- A person's ideology
- Levels of democracy

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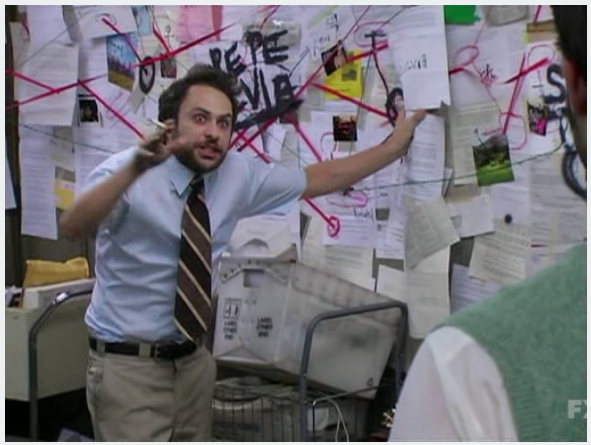

Not directly observable

- A person's ideology
- Levels of democracy
- Extent of gerrymandering

Example

- Concept: presidential approval.

Example

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- Conceptual definition:

Example

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- Conceptual definition:
    - Extent to which US adults support the actions and policies of the current US president.

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- Operational definition:

Example

- Concept: presidential approval.
- Conceptual definition:
    - Extent to which US adults support the actions and policies of the current US president.
- Operational definition:
    - “On a scale from 1 to 5, where 1 is least supportive and 5 is more supportive, how much would you say you support the job that Joe Biden is doing as president?”

Measurement error

Table 1
Response to citizenship question across two-waves of CCES panel.

Response in 2010	Response in 2012	Number of respondents	Percentage
Citizen	Citizen	18,737	99.25
Citizen	Non-Citizen	20	0.11
Non-Citizen	Citizen	36	0.19
Non-Citizen	Non-Citizen	85	0.45

- **Measurement error**: chance variation in our measurements.

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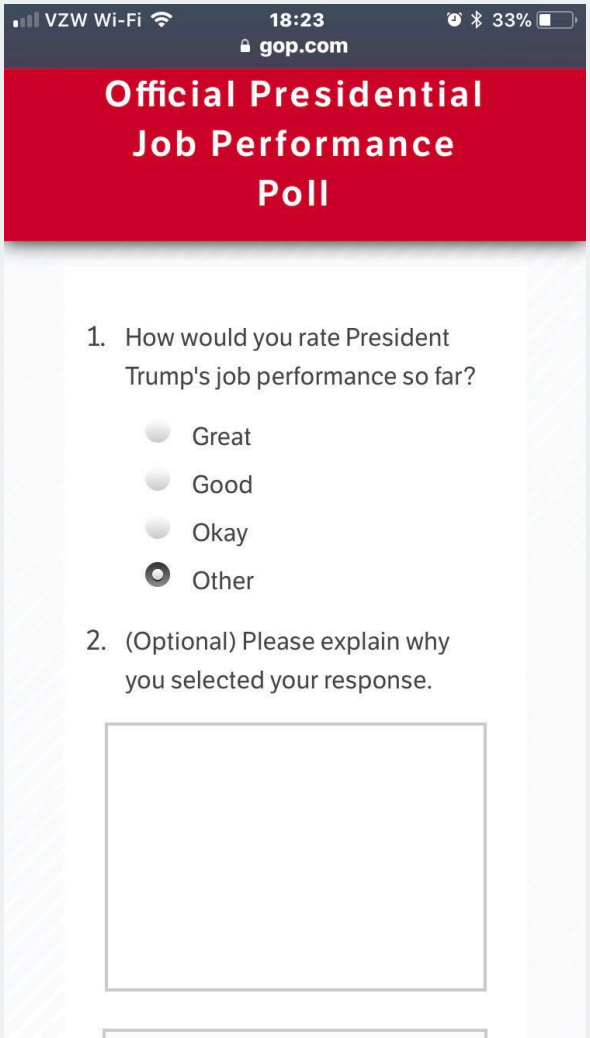
  - chance errors tend to cancel out when we take averages.
  - why? often data entry errors or faulty memories.

Bias



- **Bias**: systematic errors for all units in the same direction.

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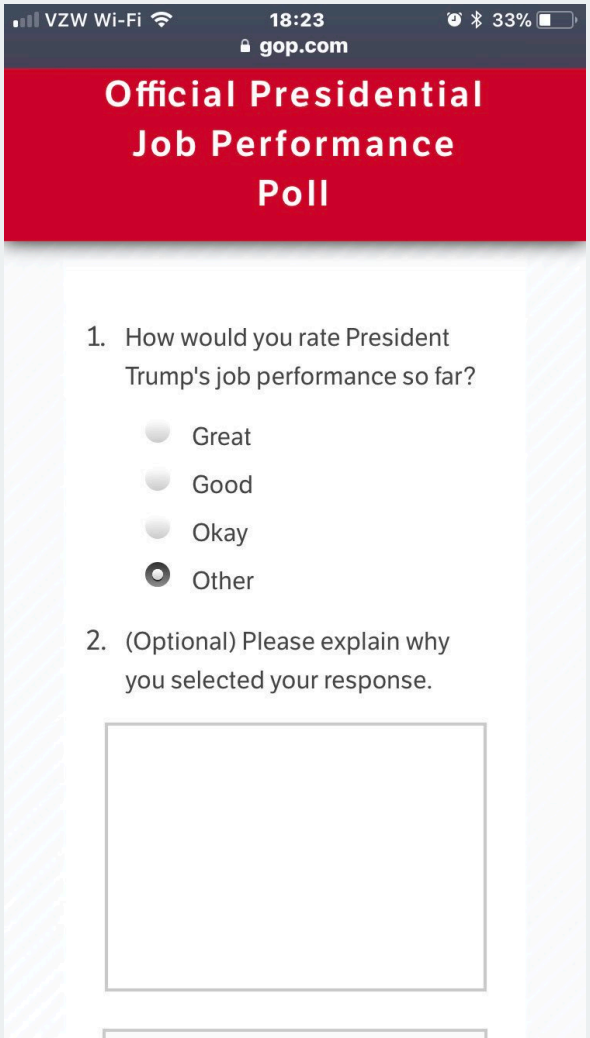

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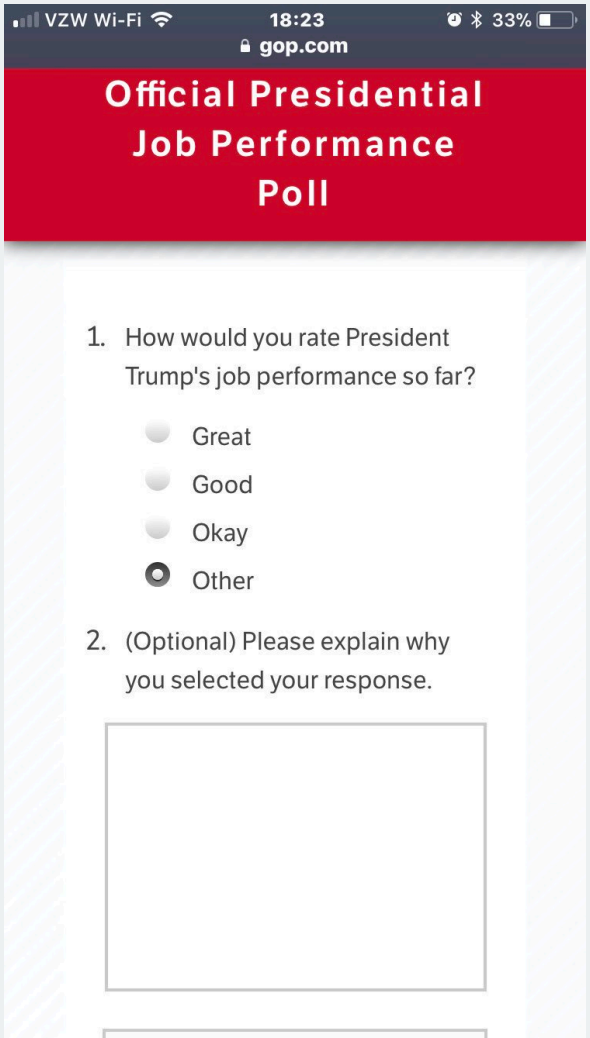
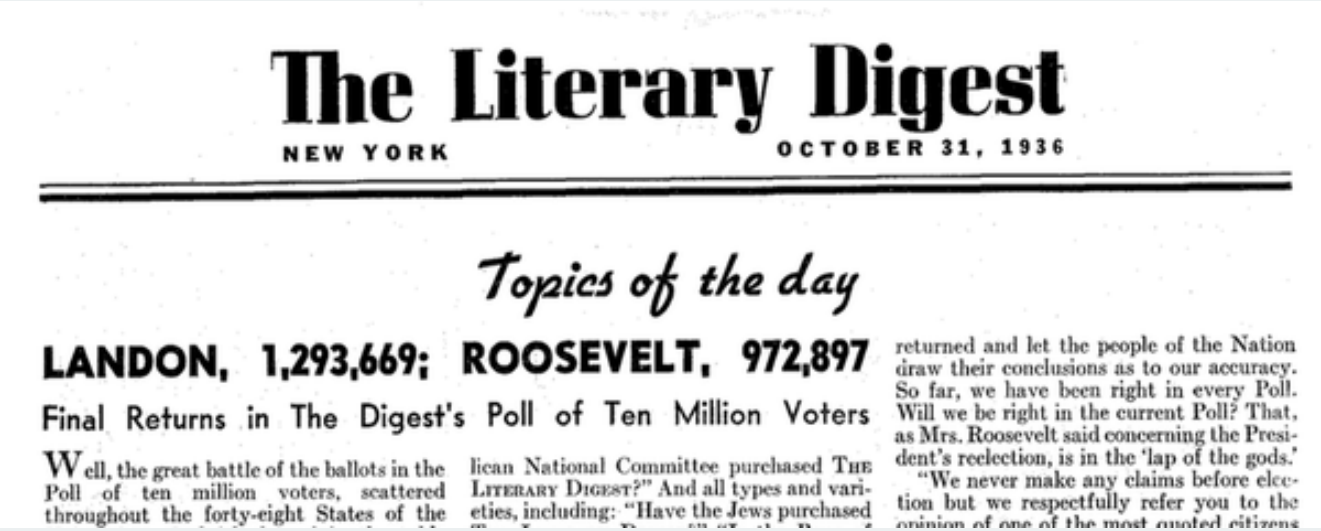


- **Bias**: systematic errors for all units in the same direction.
- individual measurement = exact value + bias + chance error.
- "What did you eat yesterday?" $\rightsquigarrow$ underreporting

1936 Literary Digest Poll



The Literary Digest

NEW YORK OCTOBER 31, 1936

Topics of the day

LANDON, 1,293,669; ROOSEVELT, 972,897

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Well, the great battle of the ballots in the Poll of ten million voters, scattered throughout the forty-eight States of the

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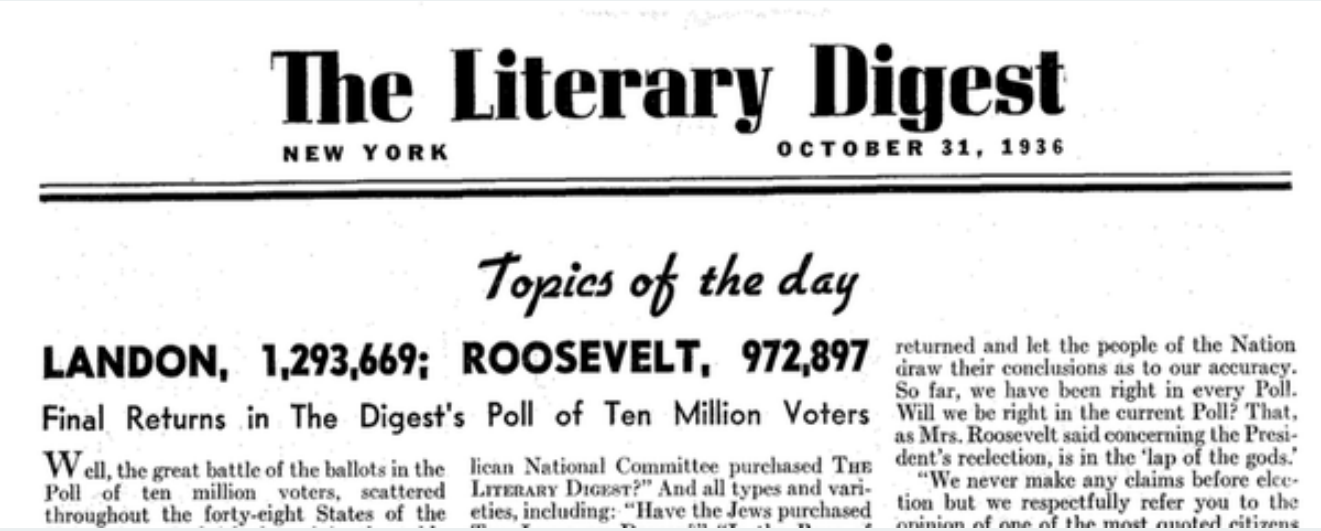

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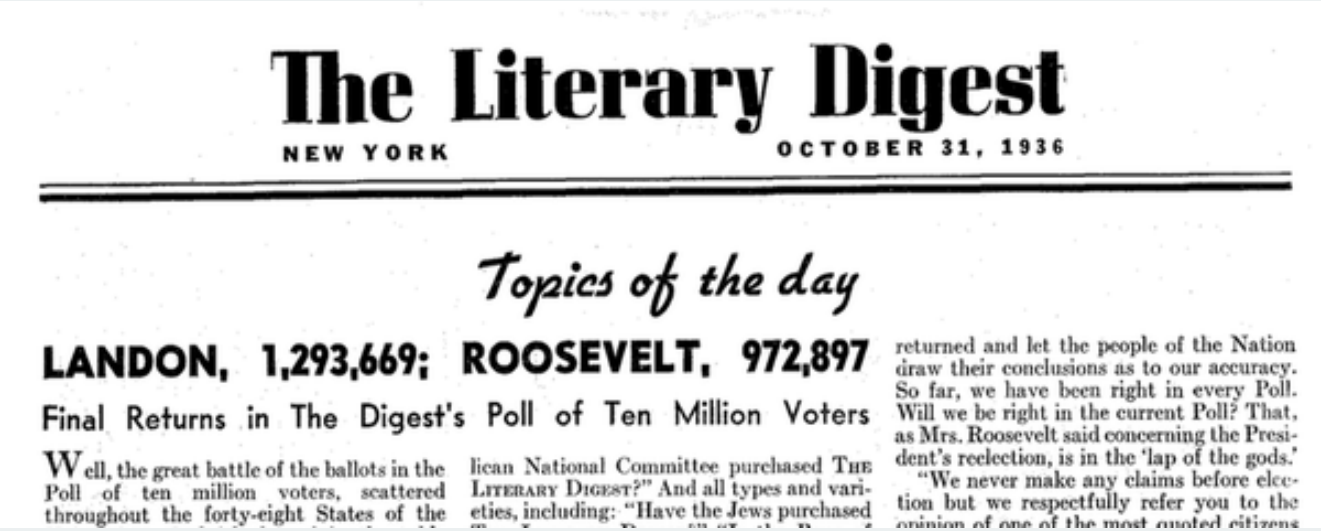

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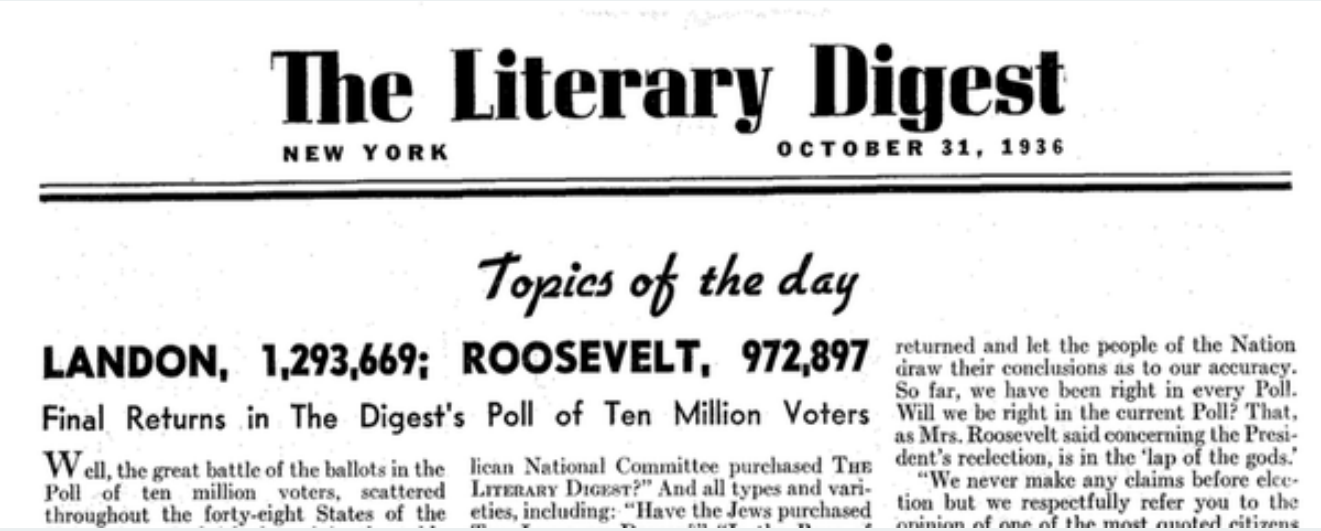

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- Source of addresses: automobile registrations, phone books, etc.
- In 1936, sent out 10 million ballots, over 2.3 million returned.
- George Gallup used only 50,000 respondents.

Poll fail

	FDR's Vote Share
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- **Nonresponse bias**: respondents differ from nonrespondents.
- $\rightsquigarrow$ when selection procedure is biased, adding more units won't help!

1948 Election

The Polling Disaster

	Truman	Dewey	Thurmond	Wallace
Crossley	45	50	2	3
Gallup	44	50	2	4
Roper	38	53	5	4
Actual	50	45	3	2

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    - Correct for potential sampling bias via statistical methods.