

# Day 09: Data Wrangling Part 2

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27 March, 2023

# Announcements

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- project update tomorrow
  - » see slack
  - » any questions
- PS08 posted tomorrow
  - » will include some regex practice

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Last time

## Base R apply family

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The basic structure is like this (from help file)

```
apply(X, MARGIN, FUN, ...)
```

- X is an “array,” so usually **matrices** (a 2-dimensional array)
- MARGIN controls how the matrix is analyzed. Should the function be executed on each **row** (margin=1) or each **column** (margin=2)?
- FUN is the **function** you want done on each row/column/whatever.
  - » *functions are objects, so they can be passed as arguments*
- ... refers to any argument you want to pass onto FUN

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## Example

Thing to remember: you are passing a function (ex: `sum`) as an argument to the `apply` function.

```
ex_mat <- matrix(rep(1:3, 3), ncol = 3)
ex_mat
```

```
##      [,1] [,2] [,3]
## [1,]    1    1    1
## [2,]    2    2    2
## [3,]    3    3    3
```

```
# Sum each row
apply(ex_mat, 1, sum)
```

```
## [1] 3 6 9
```

```
# Sum each column
apply(ex_mat, 2, sum)
```

```
## [1] 6 6 6
```

## Example

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# Sum each row
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plyr

# The plyr package

- Consistent naming protocols for the functions to know what you are putting in and taking out.

a\_ply, aapply, adply, alply, d\_ply, daply, ddply, dlply, l\_ply,  
laply, llply, m\_ply, maply, mdply, mply

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`a_ply`, `aapply`, `adply`, `alply`, `d_ply`, `dapply`, `ddply`, `dlply`, `l_ply`,  
`laply`, `llply`, `m_ply`, `maply`, `mdply`, `mlply`

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`laply`, `llply`, `m_ply`, `maply`, `mdply`, `mlply`

## Example

```
library(plyr)
x <- list(1, 2, 3, 4, 5)
ldply(x, function(x) x +1)
```

```
##    V1
## 1    2
## 2    3
## 3    4
## 4    5
## 5    6
```

dplyr



# Using dplyr

- Subset data by rows: `filter`
- Reorder by rows: `arrange`
- Subset data by column: `select`
- Create new variables as a function of other variables: `mutate`
- Collapse values down (or extract statistic): `summarise`
- We can use `group_by` to make changes in the scope

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tidyr



## Piping

- The tidyverse includes a nice syntax for combining multiple commands so we don't have to create new objects all of the time.
- The %>% syntax allows us to pass on the results of one line to another

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:plyr':
```

```
##
```

```
##      arrange, count, desc, failwith, id, mutate, rename, summar
```

```
##      summarize
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##      filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      intersect, setdiff, setequal, union
```

```
## Rows: 16661 Columns: 33
```

```
## -- Column specification -----
```

```
## Delimiter: ","
```

## Another example

```
basicPolls %>%  
  group_by(candidate_name, state) %>%  
  summarise(average_candidate = mean(pct), count = n()) %>%  
  filter(count>10)
```

```
## # A tibble: 206 x 4  
## # Groups:   candidate_name [44]  
##   candidate_name state      average_candidate count  
##   <chr>           <chr>           <dbl> <int>  
## 1 Amy Klobuchar California      1.74     40  
## 2 Amy Klobuchar Florida        1.98     13  
## 3 Amy Klobuchar Iowa           5.97     61  
## 4 Amy Klobuchar Nevada         1.71     15  
## 5 Amy Klobuchar New Hampshire  5.42     84  
## 6 Amy Klobuchar Pennsylvania  1.53     11  
## 7 Amy Klobuchar South Carolina 1.27     34  
## 8 Amy Klobuchar Texas          1.47     23  
## 9 Amy Klobuchar Wisconsin    2.52     16  
## 10 Amy Klobuchar <NA>         1.62    503  
## # ... with 196 more rows
```

## Another example

```
primaryPolls %>%  
  group_by(candidate_name, state) %>%  
  summarise(average_candidate = mean(pct), count = n()) %>%  
  filter(count > 10) %>%  
  mutate(average_prop = average_candidate/100) %>%  
  select(average_prop, candidate_name, state, count)
```

```
## # A tibble: 206 x 4  
## # Groups:   candidate_name [44]  
##   average_prop candidate_name state      count  
##           <dbl> <chr>      <chr>    <int>  
## 1      0.0174 Amy Klobuchar California    40  
## 2      0.0198 Amy Klobuchar Florida      13  
## 3      0.0597 Amy Klobuchar Iowa        61  
## 4      0.0171 Amy Klobuchar Nevada       15  
## 5      0.0542 Amy Klobuchar New Hampshire  84  
## 6      0.0153 Amy Klobuchar Pennsylvania  11  
## 7      0.0127 Amy Klobuchar South Carolina 34  
## 8      0.0147 Amy Klobuchar Texas        23  
## 9      0.0252 Amy Klobuchar Wisconsin    16  
## 10     0.0162 Amy Klobuchar <NA>       503
```

New today: pivots

# Basic pivots

- In many cases the data is not quite organized the way we want.
- Right now we have each poll as a separate row. But what if we want each candidate to be a row so we can analyze their trends in polls over time?
- Or what if we get the trend line and want to instead reorganize to look at each poll separately?
- The key commands here are `pivot_wider` and `pivot_longer`

Examples in this section from [here](#)

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Examples in this section from [here](#)

## Let's speak the same language

- Each **variable** is a column
- Each **observation** is a row
- Each **value** is a cell

Let's draw how this looks for our data

```
## # A tibble: 4 x 3
##   poll_id candidate_name      pct
##   <dbl> <chr>             <dbl>
## 1   63512 Bernard Sanders      28
## 2   63512 Andrew Yang         5
## 3   63512 Pete Buttigieg     26
## 4   63512 Joseph R. Biden Jr.  9
```

```
## # A tibble: 4 x 3
##   poll_id candidate_name      pct
##   <dbl> <chr>             <dbl>
## 1   63511 Bernard Sanders      20
## 2   63511 Joseph R. Biden Jr.  17
## 3   63511 Michael Bloomberg    15
## 4   63511 Elizabeth Warren    11
```

## Let's draw

What should our data look like for these RQs:

- For each candidate, how has their polling changed over time in Nevada? (time series)
- Do poll characteristics (like who the polling agency is) correlated with who they find as leader in Nevada?

## Example

```
nevadaPrimaries <- primaryPolls %>%  
  filter(candidate_name %in% c("Amy Klobuchar", "Bernard Sanders"  
                              "Elizabeth Warren", "Joseph R. Bid  
                              "Michael Bloomberg", "Pete Buttigi  
  filter(state == "Nevada") %>%  
  select(poll_id, candidate_name, pct, start_date)  
nevadaPrimaries
```

```
## # A tibble: 76 x 4
```

##		poll_id	candidate_name	pct	start_date
##		<dbl>	<chr>	<dbl>	<date>
##	1	63269	Joseph R. Biden Jr.	19.4	2020-01-08
##	2	63269	Bernard Sanders	17.6	2020-01-08
##	3	63269	Elizabeth Warren	10.6	2020-01-08
##	4	63269	Pete Buttigieg	8.2	2020-01-08
##	5	63269	Amy Klobuchar	3.6	2020-01-08
##	6	63254	Elizabeth Warren	14	2020-01-06
##	7	63254	Bernard Sanders	29	2020-01-06
##	8	63254	Joseph R. Biden Jr.	28	2020-01-06
##	9	63254	Pete Buttigieg	6	2020-01-06
##	10	63254	Amy Klobuchar	4	2020-01-06

# Pivot wider

- Like our time series example

country	year	cases
Angola	1999	800
Angola	2000	750
Angola	2001	925
Angola	2002	1020
India	1999	20100
India	2000	25650
India	2001	26800
India	2002	27255
Mongolia	1999	450
Mongolia	2000	512
Mongolia	2001	510
Mongolia	2002	586

country	1999	2000	2001	2002
Angola	800	750	925	1020
India	20100	25650	26800	27255
Mongolia	450	512	510	586

**Pivot data wider**

```
data %>%  
  pivot_wider(  
    names_from = "year",  
    values_from = "cases"  
  )
```

## Our example

```
wide_nv <- nevadaPrimaries %>%  
  pivot_wider(  
    id_cols = candidate_name,  
    names_from = poll_id,  
    values_from = pct)  
# dropped unused by default  
wide_nv
```

```
## # A tibble: 6 x 16  
##   candidate_name `63269` `63254` `63245` `62629` `62643` `625  
##   <chr>          <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <d  
## 1 Joseph R. Bid~    19.4    28    23    24    33    2  
## 2 Bernard Sande~    17.6    29    17    18    23    1  
## 3 Elizabeth War~    10.6    14    12    18    21    2  
## 4 Pete Buttigieg     8.2     6     6     8     9  
## 5 Amy Klobuchar      3.6     4     2     2     2  
## 6 Michael Bloom~    NA      NA     2    NA    NA    N  
## # ... with 7 more variables: `59640` <dbl>, `59508` <dbl>, `5  
## #   `58876` <dbl>, `58427` <dbl>, `58069` <dbl>, `57799` <dbl>
```

## Our example, but with dates as column names

Time series

```
wide_nv2 <- nevadaPrimaries %>%  
  pivot_wider(  
    id_cols = candidate_name,  
    names_from = start_date,  
    values_from = pct)  
wide_nv2
```

```
## # A tibble: 6 x 16
```

```
##   candidate_name 2020--~1 2020--~2 2020--~3 2019--~4 2019--~5 2019--~6  
##   <chr>          <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>  
## 1 Joseph R. Bid~ 19.4      28      23      24      33      2  
## 2 Bernard Sande~ 17.6      29      17      18      23      1  
## 3 Elizabeth War~ 10.6      14      12      18      21      2  
## 4 Pete Buttigieg 8.2        6       6       8       9  
## 5 Amy Klobuchar  3.6        4       2       2       2  
## 6 Michael Bloom~ NA         NA       2      NA      NA      NA  
## # ... with 7 more variables: `2019-09-19` <dbl>, `2019-08-28` <dbl>,  
## #   `2019-08-14` <dbl>, `2019-08-02` <dbl>, `2019-06-06` <dbl>,  
## #   `2019-05-09` <dbl>, `2019-03-28` <dbl>, and abbreviated4v  
## #   `2020-01-08` <dbl>, `2020-01-06` <dbl>, `2020-01-05` <dbl>, `2020-01-04` <dbl>
```

Pivote longer



# Pivote longer

country	1999	2000	2001	2002
Angola	800	750	925	1020
India	20100	25650	26800	27255
Mongolia	450	512	510	586

## Pivot data longer

```
data %>%  
  pivot_longer(  
    cols = 1999:2002,  
    names_to = "year",  
    values_to = "cases"  
  )
```



country	year	cases
Angola	1999	800
Angola	2000	750
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Angola	2002	1020
India	1999	20100
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India	2002	27255
Mongolia	1999	450
Mongolia	2000	512
Mongolia	2001	510
Mongolia	2002	586

## Our example

- Of course sometimes we want to do the reverse using `pivot_longer`

```
long_nv <- wide_nv2 %>%  
  # select two dates to demonstrate  
  select(candidate_name, "2020-01-08", "2020-01-06") %>%  
  pivot_longer(  
    cols = c("2020-01-08", "2020-01-06"),  
    names_to = "start_date",  
    values_to = "pct")  
long_nv
```

```
## # A tibble: 12 x 3  
##   candidate_name      start_date    pct  
##   <chr>             <chr>      <dbl>  
## 1 Joseph R. Biden Jr. 2020-01-08  19.4  
## 2 Joseph R. Biden Jr. 2020-01-06   28  
## 3 Bernard Sanders     2020-01-08  17.6  
## 4 Bernard Sanders     2020-01-06  29  
## 5 Elizabeth Warren    2020-01-08  10.6  
## 6 Elizabeth Warren    2020-01-06  14  
## 7 Pete Buttigieg      2020-01-08   8.2  
## 8 Pete Buttigieg      2020-01-06   6
```