Tidy-Tou[R]

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► General motivation

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- ► tidyr

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- ▶ Do as little "by hand" manipulation of data as possible
- ► Make your code fast and readable

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- ▶ 10 ways to do everything (isn't R awesome?!?!)
- ► There's strength in continuity and consistency

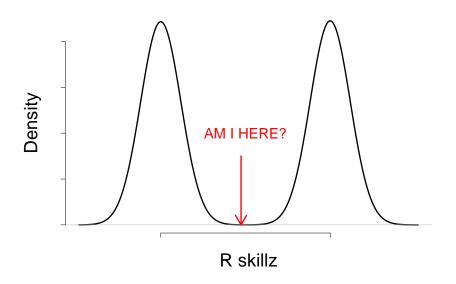
- You might find yourself saying, "That's cool and all, but I prefer . . . "
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- ► Hadley (usually) knows best

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- ▶ 10 ways to do everything (isn't R awesome?!?!)
- There's strength in continuity and consistency
- Hadley (usually) knows best
- ▶ Who?

Free book: Google "R for data science"



Who is my audience today?



The curse of data, data1, data2 ...

```
data <- read.csv("datafile")
data1 <- data[,c(1,2,3)]
data2 <- subset(data1, column1 == "test")
data3 <- ...</pre>
```



Life is better with %>% (pipe)

Simple example with %>%

```
iris[,3:5] %>%
  head(5)
```

```
##
     Petal.Length Petal.Width Species
## 1
              1.4
                          0.2 setosa
              1.4
                          0.2 setosa
## 2
## 3
              1.3
                          0.2 setosa
## 4
              1.5
                          0.2 setosa
## 5
              1.4
                          0.2 setosa
```

Emphasis on verbs instead of nouns

```
subject %>% (then)
action1 %>% (then)
action2 %>% (then)
action3
```

Exercise

Get the 5th to last row of the iris dataframe using %>% twice (there are much better ways to achieve this – just for practice)

My solution

```
iris[,3:5] %>%
  tail(5) %>%
  head(1)
```

```
## Petal.Length Petal.Width Species
## 146 5.2 2.3 virginica
```

Using %>%

Benefits of approach include:

Readability

Scalability

Consistency

Ease of use



Make some example data

make data loooong

	duck	goose	idx
1	-1.17	-0.24	1
2	-0.46	-0.63	2
3	0.65	-2.49	3
4	-0.40	-0.66	4
5	-1.09		5

make data loooong

► What's the problem?

	duck	goose	idx
1	-1.17	-0.24	1
2	-0.46	-0.63	2
3	0.65	-2.49	3
4	-0.40	-0.66	4
5	-1.09		5

make data loooong

► How do we fix it?

	duck	goose	idx
1	-1.17	-0.24	1
2	-0.46	-0.63	2
3	0.65	-2.49	3
4	-0.40	-0.66	4
5	-1.09		5

tidyr::gather() makes data frames long

```
ducks_td <- ducks %>%
  gather(key = "bird_type", value = "temp", -idx) %>%
  drop_na()
```

	idx	bird_type	temp
1	1	duck	-1.17
2	2	duck	-0.46
3	3	duck	0.65
4	4	duck	-0.40
5	5	duck	-1.09
6	1	goose	-0.24
7	2	goose	-0.63
8	3	goose	-2.49
9	4	goose	-0.66

tidyr::spread() makes data wide (sometimes useful)

```
ducks_wd <- ducks_td %>%
    spread(bird_type, temp)
```

	idx	duck	goose
1	1	-1.17	-0.24
2	2	-0.46	-0.63
3	3	0.65	-2.49
4	4	-0.40	-0.66
5	5	-1.09	

Exercise

► Check out the VADeaths data matrix (comes with base r)

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- ► Check out the VADeaths data matrix (comes with base r)
- ▶ Make VADeaths a data frame, then make it long

One solution

```
data.frame(VADeaths) %>%
  gather(key = "municipal.sex", value = "deaths_K") %>%
  head(5)
```

```
## municipal.sex deaths_K
## 1 Rural.Male 11.7
## 2 Rural.Male 18.1
## 3 Rural.Male 26.9
## 4 Rural.Male 41.0
## 5 Rural.Male 66.0
```

tidyr::separate() to split a single variable into multiple

```
## munic sx deaths_K
## 1 Rural Male 11.7
## 2 Rural Male 18.1
## 3 Rural Male 26.9
## 4 Rural Male 41.0
## 5 Rural Male 66.0
```



dplyr

dplyr can do more than what I could show in 50 minutes

dplyr

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dplyr

- dplyr can do more than what I could show in 50 minutes
- ▶ I still have a lot to learn about the functions
- Let's talk about a few

dplyr::select() for accessing columns

```
#by index, name, or mixture of two
iris %>%
  select(1, Petal.Length) %>%
  head(5)
```

```
##
    Sepal.Length Petal.Length
                       1.4
## 1
            5.1
            4.9
                      1.4
## 2
            4.7
                     1.3
## 3
## 4
            4.6
                      1.5
            5.0
                   1.4
## 5
```

dply::arrange() for ordering rows

```
#desc() for descending order
iris %>%
  arrange(Species, Sepal.Width, desc(Sepal.Length)) %>%
  select(Sepal.Width, Sepal.Length, Species) %>%
  head(5)
```

```
##
     Sepal.Width Sepal.Length Species
             2.3
## 1
                          4.5 setosa
             2.9
                          4.4 setosa
## 2
            3.0
                          5.0 setosa
## 3
            3.0
                          4.9 setosa
## 4
## 5
            3.0
                          4.8 setosa
```

dply::filter() is like base r's subset()

```
#notice all columns would be returned w/o pipe to select()
iris %>%
  filter(Species == "setosa", Sepal.Length < 6) %>%
  select(Sepal.Length, Species) %>%
  head(5)
```

```
## Sepal.Length Species
## 1 5.1 setosa
## 2 4.9 setosa
## 3 4.7 setosa
## 4 4.6 setosa
## 5 5.0 setosa
```

dply::mutate() add new columns

```
iris %>%
  mutate(Sepal.Area = Sepal.Length * Sepal.Width) %>%
  select(Sepal.Area, Species) %>%
  head(5)
```

```
## Sepal.Area Species
## 1 17.85 setosa
## 2 14.70 setosa
## 3 15.04 setosa
## 4 14.26 setosa
## 5 18.00 setosa
```

dply::group_by() and dply::summarise()

```
## # A tibble: 3 × 5
## Species mean_SL sd_SL q25 q75
## <fctr> <dbl> <dbl> <dbl> <dbl> <dbl> 5.2
## 2 versicolor 5.936 0.5161711 5.600 6.3
## 3 virginica 6.588 0.6358796 6.225 6.9
```

dply::sample_n()

```
#also see new modelr package for more like this
iris %>%
  sample_n(2) %>%
  select(Petal.Length, Species)
```

```
## Petal.Length Species
## 98 4.3 versicolor
## 108 6.3 virginica
```

dply::sample_frac()

```
iris %>%
  sample_frac(0.02) %>%
  select(Petal.Length, Species)
```

```
## Petal.Length Species
## 97 4.2 versicolor
## 144 5.9 virginica
## 14 1.1 setosa
```

group_by() and n()

```
#surprisingly hard in base R
iris %>%
  group_by(Species) %>%
 mutate(counts = n()) %>%
  select(Species, counts) %>%
  sample_n(2)
## Source: local data frame [6 x 2]
## Groups: Species [3]
##
##
       Species counts
##
        <fctr> <int>
                   50
## 1
        setosa
## 2
        setosa 50
## 3 versicolor 50
## 4 versicolor 50
    virginica
                   50
```

Exercise

Using the tidy version of VADeaths, generate a mean and variance for the number of deaths for each municipal-sex combination (group by municipality and sex, *then* computer the mean and standard deviation of deaths).

One solution

Result

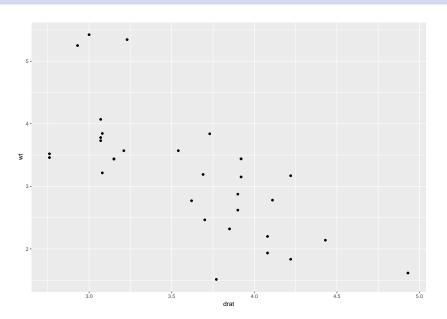
	munic	SX	mean_death	sd_death
1	Rural	Female	25.18	18.42
2	Rural	Male	32.74	21.60
3	Urban	Female	25.28	17.06
4	Urban	Male	40.48	22.58



ggplot2 template

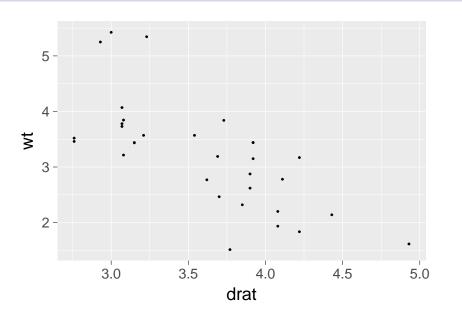
```
#default:
ggplot(data = <DATA>) +
  <GEOM FUNCTION>(mapping = aes(<MAPPINGS>))
#alternative 1:
<DATA> %>%
 ggplot()+
  <GEOM_FUNCTION>(mapping = aes(<MAPPINGS>))
#alternative 2 (my usual preference):
<DATA> %>%
  ggplot(mapping = aes(<MAPPINGS>)) +
  <GEOM FUNCTION>()
```

```
p <- mtcars %>%
  ggplot(aes(x = drat, y = wt)) +
  geom_point()
```

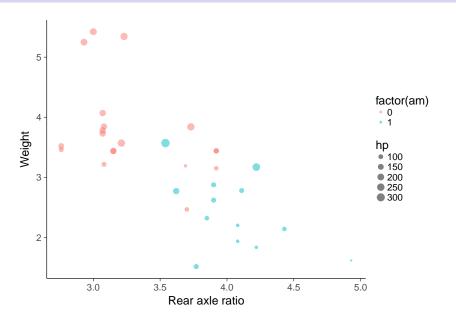


Looks bad on my screen, but easy to fix

```
p <- mtcars %>%
  ggplot(aes(x = drat, y = wt)) +
  geom_point() +
  theme_gray(base_size = 30)
```

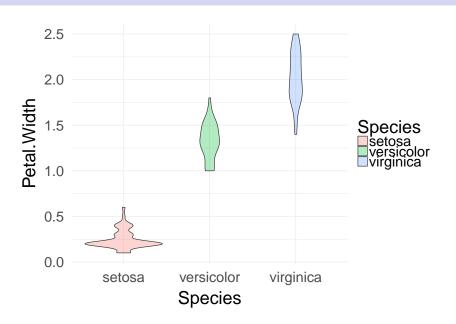


```
p <- mtcars %>%
  ggplot(aes(x = drat, y = wt, size = hp)) +
  geom_point(aes(colour = factor(am)), alpha = 0.5) +
  xlab("Rear axle ratio") +
  ylab("Weight") +
  theme_classic(base_size = 20)
```



violin plots are cool!

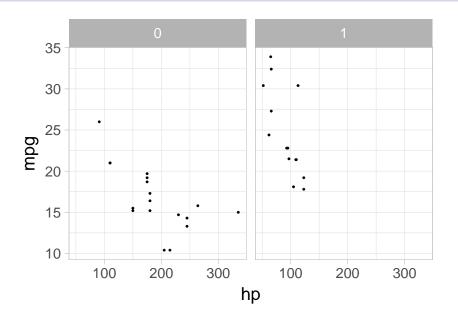
Result



Plots with multiple panels

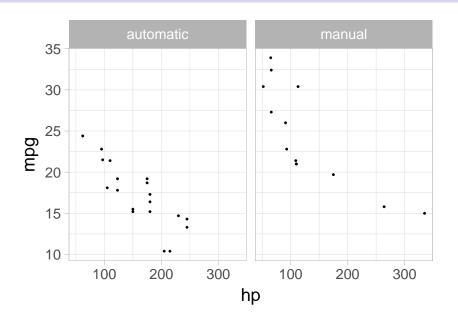
```
p <- mtcars %>%
  ggplot(aes(x = hp, y = mpg)) +
  geom_point() +
  facet_wrap(~ vs) +
  theme_light(base_size = 30)
```

Result



Plots with multiple panels

Result



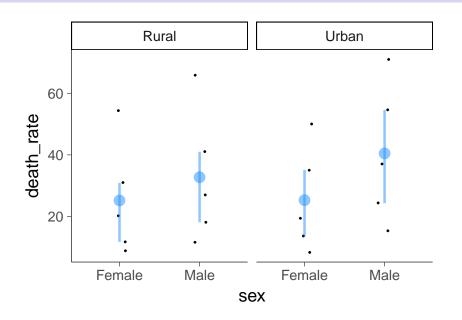
Exercise

Using the tidiest version of VADeaths, make a plot of death rate by sex, with panels for municipal

My solution

```
p <- data.frame(VADeaths) %>%
  mutate(age_group = rownames(VADeaths)) %>%
  gather("pop_group", "death_rate", -age_group) %>%
  separate(pop group, c("municipal", "sex"),
           sep = "\\.") %>%
  ggplot(aes(x = sex, y = death_rate)) + #new stuff below
  geom jitter(width = 0.1) +
  facet grid(~municipal) +
  geom pointrange(stat = "summary",
              fun.ymin = function(z) quantile(z, 0.25),
              fun.ymax = function(z) quantile(z, 0.75),
              fun.y = mean, colour = "dodgerblue",
              alpha = 0.5, lwd = 2) +
  theme classic(base size = 30)
```

Result



purrr:functional programming (like

lapply/sapply, but safer)

Explicit loops are slow (in R) and tedious to write

```
#for example
vec <- 1:4

store <- rep(NA, length(vec))
for(i in vec){
   store[i] <- i*2
}
store</pre>
```

[1] 2 4 6 8

functional "loop" version

```
vec <- 1:4
vec %>%
  map_dbl(function(x) x * 2)
## [1] 2 4 6 8
# or
vec %>%
 map_dbl(~.x * 2)
## [1] 2 4 6 8
```

But don't do either of the above for this (vec*2)

▶ map() - returns a list

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- map_int() returns a vector of integers
- map_df() returns a dataframe

Important to understand lists and other data types

```
my_list <- list(1, TRUE, rnorm(2), "lists!!")
#access with double brackets [[]]
my_list[[3]]</pre>
```

[1] 0.8921948 0.6784726

purrr::map()

```
#I() is the identity function
#same as function(x) x
my_list %>%
 map(I)
## [[1]]
## [1] 1
##
## [[2]]
## [1] TRUE
##
## [[3]]
## [1] 0.8921948 0.6784726
##
## [[4]]
## [1] "lists!!"
```

purrr::map_dbl()

```
mtcars %>%
  map_dbl(mean) %>%
  head(5)
```

```
## mpg cyl disp hp drat
## 20.090625 6.187500 230.721875 146.687500 3.596563
```

```
purrr::map_lgl()
```

```
mtcars %>%
  map_lgl(is.numeric) %>%
  head(5)
```

```
## mpg cyl disp hp drat
## TRUE TRUE TRUE TRUE TRUE
```

purrr::map_int()

```
mtcars %>%
  map_int(length) %>%
  head(5)
```

```
## mpg cyl disp hp drat
## 32 32 32 32 32
```

purrr::map_df()

```
1:4 %>%

map_df( ~ data.frame(rbind(rnorm(3))))
```

```
## X1 X2 X3

## 1 -0.4761087 -0.2867547 0.4221558

## 2 -0.6924905 0.5708493 0.3160277

## 3 0.3623887 0.4145315 1.2019817

## 4 1.6175333 0.8349768 1.6647959
```

Here's a weird one

##

32

150

5