

Lab 4

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Lab 4 - Transforming data, cont: mutating joins

Toy data-sets

Create the toy data sets in the slides using tibble rather than tribble

Band d.s.

```
band <- tibble(  
  name = c("Mick", "John", "Paul"),  
  band = c("Stones", "Beatles", "Beatles")  
)  
  
band
```

```
# A tibble: 3 x 2  
  name   band  
  <chr> <chr>  
1 Mick   Stones  
2 John   Beatles  
3 Paul   Beatles
```

Instruments d.s.

```
instrument <- tibble(
  name = c("John", "Paul", "Keith"),
  band = c("Guitar", "Bass", "Guitar")
)

instrument

# A tibble: 3 x 2
  name   band
  <chr> <chr>
1 John   Guitar
2 Paul   Bass
3 Keith  Guitar
```

Experiment with the various joins as in the examples

Left Join

```
band %>%
  left_join(instrument, by = "name")
```

```
# A tibble: 3 x 3
  name   band.x band.y
  <chr> <chr>  <chr>
1 Mick   Stones <NA>
2 John   Beatles Guitar
3 Paul   Beatles Bass
```

Right join

```
band %>%
  right_join(instrument, by = "name")
```

```
# A tibble: 3 x 3
  name   band.x band.y
  <chr> <chr>  <chr>
1 John   Beatles Guitar
2 Paul   Beatles Bass
3 Keith  <NA>    Guitar
```

Full Join

```
band %>%
  full_join(instrument, by = "name")
```

```
# A tibble: 4 x 3
  name band.x band.y
  <chr> <chr>   <chr>
1 Mick Stones <NA>
2 John Beatles Guitar
3 Paul Beatles Bass
4 Keith <NA>    Guitar
```

Inner

```
band %>%
  inner_join(instrument, by = "name")
```

```
# A tibble: 2 x 3
  name band.x band.y
  <chr> <chr>   <chr>
1 John Beatles Guitar
2 Paul Beatles Bass
```

NYC Flights Data-set

Use `data(package = "nycflights13")` to see the included data sets.

```
data(package = "nycflights13")
```

Use `skimr` package to inspect data frames

```
skim(flights)
```

Table 1: Data summary

Name	flights
Number of rows	336776
Number of columns	19
Column type frequency:	
character	4
numeric	14
POSIXct	1
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
carrier	0	1.00	2	2	0	16	0
tailnum	2512	0.99	5	6	0	4043	0
origin	0	1.00	3	3	0	3	0
dest	0	1.00	3	3	0	105	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
year	0	1.00	2013.00	0.00	2013	2013	2013	2013	2013	
month	0	1.00	6.55	3.41	1	4	7	10	12	
day	0	1.00	15.71	8.77	1	8	16	23	31	
dep_time	8255	0.98	1349.11	488.28	1	907	1401	1744	2400	
sched_dep_time	0	1.00	1344.25	467.34	106	906	1359	1729	2359	
dep_delay	8255	0.98	12.64	40.21	-43	-5	-2	11	1301	
arr_time	8713	0.97	1502.05	533.26	1	1104	1535	1940	2400	
sched_arr_time	0	1.00	1536.38	497.46	1	1124	1556	1945	2359	
arr_delay	9430	0.97	6.90	44.63	-86	-17	-5	14	1272	
flight	0	1.00	1971.92	1632.47	1	553	1496	3465	8500	
air_time	9430	0.97	150.69	93.69	20	82	129	192	695	
distance	0	1.00	1039.91	733.23	17	502	872	1389	4983	
hour	0	1.00	13.18	4.66	1	9	13	17	23	
minute	0	1.00	26.23	19.30	0	8	29	44	59	

Variable type: POSIXct

skim_variable	n_missing	complete_rate	min	max	median	n_unique
time_hour	0	1	2013-01-01 05:00:00	2013-12-31 23:00:00	2013-07-03 10:00:00	6936

`skim(airlines)`

Table 5: Data summary

Name	airlines
Number of rows	16
Number of columns	2
<hr/>	
Column type frequency:	
character	2
<hr/>	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
carrier	0	1	2	2	0	16	0
name	0	1	9	27	0	16	0

`skim(weather)`

Table 7: Data summary

Name	weather
Number of rows	26115
Number of columns	15
<hr/>	
Column type frequency:	
character	1
numeric	13
POSIXct	1
<hr/>	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
origin	0	1	3	3	0	3	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
year	0	1.00	2013.00	0.00	2013.00	2013.00	2013.00	2013.00	2013.00	
month	0	1.00	6.50	3.44	1.00	4.00	7.00	9.00	12.00	
day	0	1.00	15.68	8.76	1.00	8.00	16.00	23.00	31.00	
hour	0	1.00	11.49	6.91	0.00	6.00	11.00	17.00	23.00	
temp	1	1.00	55.26	17.79	10.94	39.92	55.40	69.98	100.04	
dewp	1	1.00	41.44	19.39	-9.94	26.06	42.08	57.92	78.08	
humid	1	1.00	62.53	19.40	12.74	47.05	61.79	78.79	100.00	
wind_dir	460	0.98	199.76	107.31	0.00	120.00	220.00	290.00	360.00	
wind_speed	4	1.00	10.52	8.54	0.00	6.90	10.36	13.81	1048.36	
wind_gust	20778	0.20	25.49	5.95	16.11	20.71	24.17	28.77	66.75	
precip	0	1.00	0.00	0.03	0.00	0.00	0.00	0.00	1.21	
pressure	2729	0.90	1017.90	7.42	983.80	1012.90	1017.60	1023.00	1042.10	
visib	0	1.00	9.26	2.06	0.00	10.00	10.00	10.00	10.00	

Variable type: POSIXct

skim_variable	n_missing	complete_rate	min	max	median	n_unique
time_hour	0	1	2013-01-01 01:00:00	2013-12-30 18:00:00	2013-07-01 14:00:00	8714

```
skim(planets)
```

Table 11: Data summary

Name	planets
Number of rows	3322
Number of columns	9

Column type frequency:	
character	5
numeric	4
<hr/>	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
tailnum	0	1	5	6	0	3322	0
type	0	1	10	24	0	3	0
manufacturer	0	1	4	29	0	35	0
model	0	1	2	18	0	127	0
engine	0	1	7	13	0	6	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
year	70	0.98	2000.48	7.19	1956	1997.0	2001	2005	2013	
engines	0	1.00	2.00	0.12	1	2.0	2	2	4	
seats	0	1.00	154.32	73.65	2	140.0	149	182	450	
speed	3299	0.01	236.78	149.76	90	107.5	162	432	432	

```
skim(airports)
```

Table 14: Data summary

Name	airports
Number of rows	1458
Number of columns	8
<hr/>	
Column type frequency:	
character	4
numeric	4
<hr/>	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
faa	0	1	3	3	0	1458	0
name	0	1	4	51	0	1440	0
dst	0	1	1	1	0	3	0
tzone	3	1	14	19	0	9	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
lat	0	1	41.65	10.45	19.72	34.26	40.09	45.07	72.27	
lon	0	1	-29.84	103.39	-	176.65	119.19	94.66	82.52	174.11
alt	0	1	1001.42	1523.63	-	70.25	473.00	1062.50	9078.00	54.00
tz	0	1	-6.52	1.62	-	-8.00	-	-5.00	8.00	10.00 6.00

Join airlines to flights to find the names of which airlines had the largest arrival delays.

```
flights %>%
  left_join(airlines, join_by(carrier)) %>%
  select(name, arr_delay, tailnum) %>%
  arrange(desc(arr_delay))
```

```
# A tibble: 336,776 x 3
  name           arr_delay tailnum
  <chr>          <dbl>   <chr>
1 Hawaiian Airlines Inc.    1272 N384HA
2 Envoy Air            1127 N504MQ
3 Envoy Air            1109 N517MQ
4 American Airlines Inc.  1007 N338AA
5 Envoy Air             989 N665MQ
6 Delta Air Lines Inc.   931 N959DL
7 Delta Air Lines Inc.   915 N927DA
8 Delta Air Lines Inc.   895 N6716C
9 American Airlines Inc.  878 N5DMAA
```

```
10 Envoy Air          875 N523MQ
# i 336,766 more rows
```

The names of the airlines with the largest arr_delay's are: **Hawaiian Airlines Inc.**, **Envoy Air**, **American Airlines Inc.**, and **Delta Air Lines Inc.**

Use flights and airports to compute the distance and average arr_delay by destination airport (names only, not codes).

```
flights2.0 <- flights %>%
  left_join(airports, join_by(dest == name)) %>%
  group_by("Destination Airport" = dest) %>%
  summarize(
    "Average Arrival Delay" = mean(arr_delay, na.rm = TRUE),
    "Distance" = sum(distance, na.rm = TRUE)

)
flights2.0
```

```
# A tibble: 105 x 3
`Destination Airport` `Average Arrival Delay` Distance
<chr>                  <dbl>      <dbl>
1 ABQ                   4.38     463804
2 ACK                   4.85     52735
3 ALB                  14.4      62777
4 ANC                  -2.5      26960
5 ATL                  11.3     13033618
6 AUS                  6.02     3693263
7 AVL                  8.00      160485
8 BDL                  7.05      51388
9 BGR                  8.03      141750
10 BHM                 16.9      257201
# i 95 more rows
```

Population and Continents data sets, Brightspace

Join these two data sets, and create a new data frame called population_summary that contains a row for each continent and a column for the total population for that continent, in descending order of population.

```

population <- read_csv("data/population.csv")
continents <- read_csv("data/continents.csv")

population_summary <- population %>%
  left_join(continents, join_by(country == entity)) %>%
  group_by("Continents" = continent) %>%
  summarize(
    Total_Population = sum(population, na.rm = TRUE)
  ) %>%
  arrange(desc(Total_Population))
population_summary

```

```

# A tibble: 6 x 2
  Continents     Total_Population
  <chr>           <dbl>
1 Asia            4685922.
2 Africa          1424831.
3 Europe          740607.
4 North America   594415.
5 South America   437233.
6 Oceania         44752.

```

NFL attendance and standings data sets, Brightspace

Make boxplots of weekly attendance for each team

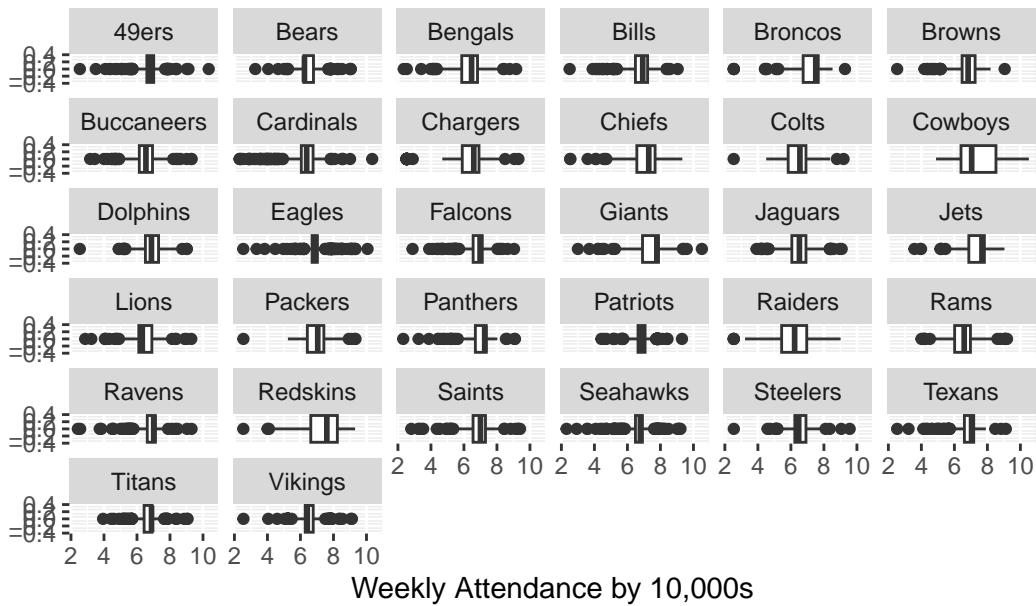
```

attendance <- read_csv("data/attendance.csv")

attendance %>%
  ggplot(aes(x = weekly_attendance)) +
  geom_boxplot() +
  labs( x = "Weekly Attendance by 10,000s",
        title = "Weekly Attendance of Each Team") +
  scale_x_continuous(label = label_number(scale = 1/10000)) +
  facet_wrap(~team_name)

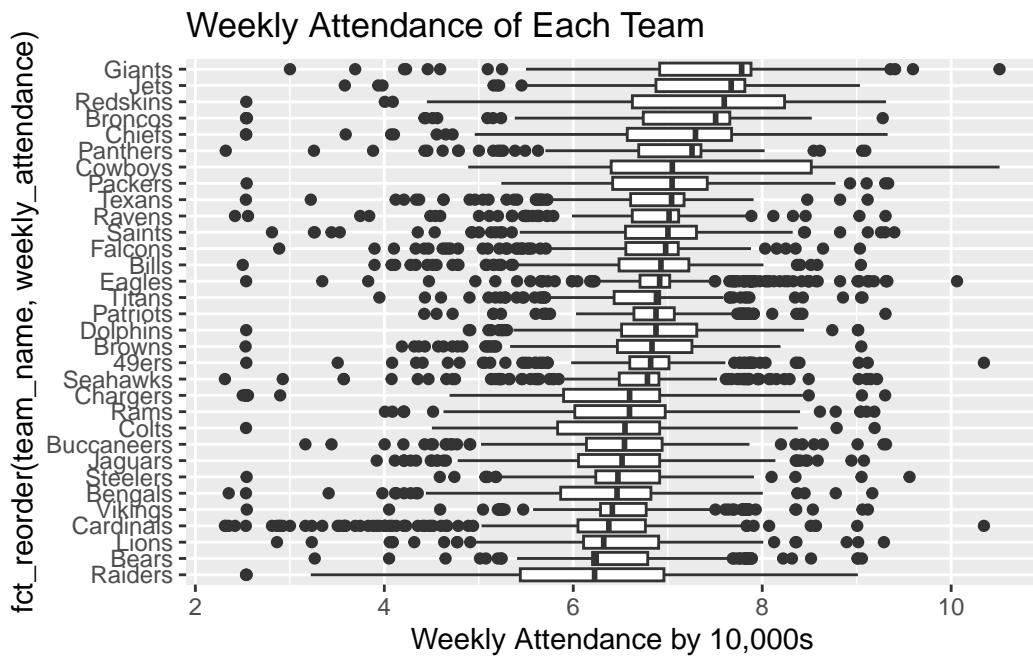
```

Weekly Attendance of Each Team



Use `fct_reorder` to order the teams according to attendance

```
attendance %>%
  ggplot(aes(y = fct_reorder(team_name, weekly_attendance), x = weekly_attendance)) +
  geom_boxplot() +
  labs( x = "Weekly Attendance by 10,000s",
        title = "Weekly Attendance of Each Team") +
  scale_x_continuous(label = label_number(scale = 1/10000))
```



Does it make sense to arrange vertically or horizontally?

It makes sense to arrange vertically because it is more visually appealing to the eye to compare this way.

Use fill = to plot side by side for playoffs vs not

```
standings <- read_csv("data/standings.csv")

attendance %>%
  left_join(standings, join_by(team_name)) %>%
  ggplot(aes(y = fct_reorder(team_name, weekly_attendance), x = weekly_attendance)) +
  geom_boxplot(aes(fill = playoffs)) +
  labs( x = "Weekly Attendance by 10,000",
        y = "Team Name",
        title = "Weekly Attendance of Each Team") +
  scale_x_continuous(label = label_number(scale = 1/10000)) +
  theme_linedraw()
```

Weekly Attendance of Each Team

