Chapter 22 Joining tables

The information we need for a given analysis may not be just in one table. For example, when forecasting elections we used the function `left_join` to combine the information from two tables. Here we use a simpler example to illustrate the general challenge of combining tables.

Suppose we want to explore the relationship between population size for US states and electoral votes. We have the population size in this table:

```
library(tidyverse)
library(dslabs)
data(murders)
head(murders)
#>        state abb region population total
#> 1    Alabama  AL  South    4779736   135
#> 2     Alaska  AK   West     710231    19
#> 3    Arizona  AZ   West    6392017   232
#> 4   Arkansas  AR  South    2915918    93
#> 5 California  CA   West   37253956  1257
#> 6   Colorado  CO   West    5029196    65
```

and electoral votes in this one:

```
data(polls_us_election_2016)
head(results_us_election_2016)
#>          state electoral_votes clinton trump others
#> 1   California              55    61.7  31.6    6.7
#> 2        Texas              38    43.2  52.2    4.5
#> 3      Florida              29    47.8  49.0    3.2
#> 4     New York              29    59.0  36.5    4.5
#> 5     Illinois              20    55.8  38.8    5.4
#> 6 Pennsylvania              20    47.9  48.6    3.6
```

Just concatenating these two tables together will not work since the order of the states is not the same.

```
identical(results_us_election_2016$state, murders$state)
#> [1] FALSE
```

The *join* functions, described below, are designed to handle this challenge.

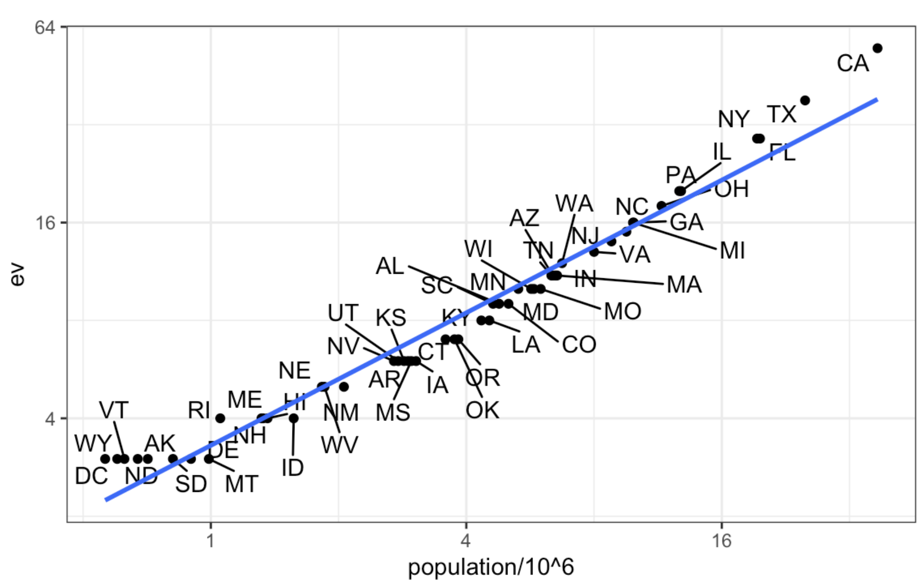
22.1 Joins

The *join* functions in the **dplyr** package make sure that the tables are combined so that matching rows are together. If you know SQL, you will see that the approach and syntax is very similar. The general idea is that one needs to identify one or more columns that will serve to match the two tables. Then a new table with the combined information is returned. Notice what happens if we join the two tables above by state using `left_join` (we will remove the `others` column and rename `electoral_votes` so that the tables fit on the page):

```r
tab <- left_join(murders, results_us_election_2016, by = "state") %>%
  select(-others) %>% rename(ev = electoral_votes)
head(tab)
#>        state abb region population total ev clinton trump
#> 1    Alabama  AL  South    4779736   135  9    34.4  62.1
#> 2     Alaska  AK   West     710231    19  3    36.6  51.3
#> 3    Arizona  AZ   West    6392017   232 11    45.1  48.7
#> 4   Arkansas  AR  South    2915918    93  6    33.7  60.6
#> 5 California  CA   West   37253956  1257 55    61.7  31.6
#> 6   Colorado  CO   West    5029196    65  9    48.2  43.3
```

The data has been successfully joined and we can now, for example, make a plot to explore the relationship:

```r
library(ggrepel)
tab %>% ggplot(aes(population/10^6, ev, label = abb)) +
  geom_point() +
  geom_text_repel() +
  scale_x_continuous(trans = "log2") +
  scale_y_continuous(trans = "log2") +
  geom_smooth(method = "lm", se = FALSE)
```



We see the relationship is close to linear with about 2 electoral votes for every million persons, but with very small states getting higher ratios.

In practice, it is not always the case that each row in one table has a matching row in the other. For this reason, we have several versions of join. To illustrate this challenge, we will take subsets of the tables above. We create the tables `tab1` and `tab2` so that they have some states in common but not all:

```
tab_1 <- slice(murders, 1:6) %>% select(state, population)
tab_1
#>        state population
#> 1    Alabama    4779736
#> 2     Alaska     710231
#> 3    Arizona    6392017
#> 4   Arkansas    2915918
#> 5 California   37253956
#> 6   Colorado    5029196
tab_2 <- results_us_election_2016 %>%
  filter(state%in%c("Alabama", "Alaska", "Arizona",
                    "California", "Connecticut", "Delaware")) %>%
  select(state, electoral_votes) %>% rename(ev = electoral_votes)
tab_2
#>         state ev
#> 1  California 55
#> 2     Arizona 11
#> 3     Alabama  9
#> 4 Connecticut  7
#> 5      Alaska  3
#> 6    Delaware  3
```

We will use these two tables as examples in the next sections.

22.1.1 Left join

Suppose we want a table like `tab_1`, but adding electoral votes to whatever states we have available. For this, we use `left_join` with `tab_1` as the first argument. We specify which column to use to match with the `by` argument.

```
left_join(tab_1, tab_2, by = "state")
#>        state population ev
#> 1    Alabama    4779736  9
#> 2     Alaska     710231  3
#> 3    Arizona    6392017 11
#> 4   Arkansas    2915918 NA
#> 5 California   37253956 55
#> 6   Colorado    5029196 NA
```

Note that `NA` s are added to the two states not appearing in `tab_2`. Also, notice that this function, as well as all the other joins, can receive the first arguments through the pipe:

```
tab_1 %>% left_join(tab_2, by = "state")
```

22.1.2 Right join

If instead of a table with the same rows as first table, we want one with the same rows as second table, we can use `right_join`:

```
tab_1 %>% right_join(tab_2, by = "state")
#>         state population ev
#> 1  California   37253956 55
#> 2     Arizona    6392017 11
#> 3     Alabama    4779736  9
#> 4 Connecticut         NA  7
#> 5      Alaska     710231  3
#> 6    Delaware         NA  3
```

Now the NAs are in the column coming from `tab_1`.

22.1.3 Inner join

If we want to keep only the rows that have information in both tables, we use `inner_join`. You can think of this as an intersection:

```
inner_join(tab_1, tab_2, by = "state")
#>        state population ev
#> 1    Alabama    4779736  9
#> 2     Alaska     710231  3
#> 3    Arizona    6392017 11
#> 4 California   37253956 55
```

22.1.4 Full join

If we want to keep all the rows and fill the missing parts with NAs, we can use `full_join`. You can think of this as a union:

```
full_join(tab_1, tab_2, by = "state")
#>         state population ev
#> 1     Alabama    4779736  9
#> 2      Alaska     710231  3
#> 3     Arizona    6392017 11
#> 4    Arkansas    2915918 NA
#> 5  California   37253956 55
#> 6    Colorado    5029196 NA
#> 7 Connecticut         NA  7
#> 8    Delaware         NA  3
```

22.1.5 Semi join

The `semi_join` function lets us keep the part of first table for which we have information in the second. It does not add the columns of the second:

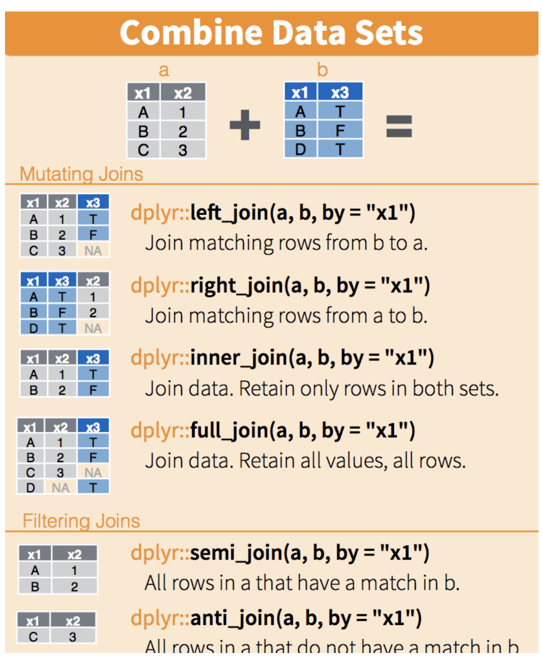
```
semi_join(tab_1, tab_2, by = "state")
#>        state population
#> 1    Alabama    4779736
#> 2     Alaska     710231
#> 3    Arizona    6392017
#> 4 California   37253956
```

22.1.6 Anti join

The function `anti_join` is the opposite of `semi_join`. It keeps the elements of the first table for which there is no information in the second:

```
anti_join(tab_1, tab_2, by = "state")
#>      state population
#> 1 Arkansas    2915918
#> 2 Colorado    5029196
```

The following diagram summarizes the above joins:



(Image courtesy of RStudio[79]. CC-BY-4.0 license[80]. Cropped from original.)

22.2 Binding

Although we have yet to use it in this book, another common way in which datasets are combined is by *binding* them. Unlike the join function, the binding functions do not try to match by a variable, but instead simply combine datasets. If the datasets don't match by the appropriate dimensions, one obtains an error.

22.2.1 Binding columns

The **dplyr** function *bind_cols* binds two objects by making them columns in a tibble. For example, we quickly want to make a data frame consisting of numbers we can use.

```
bind_cols(a = 1:3, b = 4:6)
#> # A tibble: 3 x 2
#>       a     b
#>   <int> <int>
#> 1     1     4
#> 2     2     5
#> 3     3     6
```

This function requires that we assign names to the columns. Here we chose `a` and `b`.

Note that there is an R-base function `cbind` with the exact same functionality. An important difference is that `cbind` can create different types of objects, while `bind_cols` always produces a data frame.

`bind_cols` can also bind two different data frames. For example, here we break up the `tab` data frame and then bind them back together:

```
tab_1 <- tab[, 1:3]
tab_2 <- tab[, 4:6]
tab_3 <- tab[, 7:8]
new_tab <- bind_cols(tab_1, tab_2, tab_3)
head(new_tab)
#>        state abb region population total ev clinton trump
#> 1    Alabama  AL  South    4779736   135  9    34.4  62.1
#> 2     Alaska  AK   West     710231    19  3    36.6  51.3
#> 3    Arizona  AZ   West    6392017   232 11    45.1  48.7
#> 4   Arkansas  AR  South    2915918    93  6    33.7  60.6
#> 5 California  CA   West   37253956  1257 55    61.7  31.6
#> 6   Colorado  CO   West    5029196    65  9    48.2  43.3
```

22.2.2 Binding by rows

The `bind_rows` function is similar to `bind_cols`, but binds rows instead of columns:

```
tab_1 <- tab[1:2,]
tab_2 <- tab[3:4,]
bind_rows(tab_1, tab_2)
#>      state abb region population total ev clinton trump
#> 1  Alabama  AL  South    4779736   135  9    34.4  62.1
#> 2   Alaska  AK   West     710231    19  3    36.6  51.3
#> 3  Arizona  AZ   West    6392017   232 11    45.1  48.7
#> 4 Arkansas  AR  South    2915918    93  6    33.7  60.6
```

This is based on an R-base function `rbind`.

22.3 Set operators

Another set of commands useful for combining datasets are the set operators. When applied to vectors, these behave as their names suggest. Examples are `intersect`, `union`, `setdiff`, and `setequal`. However, if the **tidyverse**, or more specifically **dplyr**, is loaded, these functions can be used on data frames as opposed to just on vectors.

22.3.1 Intersect

You can take intersections of vectors of any type, such as numeric:

```
intersect(1:10, 6:15)
#> [1]  6  7  8  9 10
```

or characters:

```
intersect(c("a","b","c"), c("b","c","d"))
#> [1] "b" "c"
```

The **dplyr** package includes an `intersect` function that can be applied to tables with the same column names. This function returns the rows in common between two tables. To make sure we use the **dplyr** version of `intersect` rather than the base package version, we can use `dplyr::intersect` like this:

```
tab_1 <- tab[1:5,]
tab_2 <- tab[3:7,]
dplyr::intersect(tab_1, tab_2)
#>        state abb region population total ev clinton trump
#> 1    Arizona  AZ   West    6392017   232 11    45.1  48.7
#> 2   Arkansas  AR  South    2915918    93  6    33.7  60.6
#> 3 California  CA   West   37253956  1257 55    61.7  31.6
```

22.3.2 Union

Similarly *union* takes the union of vectors. For example:

```
union(1:10, 6:15)
#>  [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15
union(c("a","b","c"), c("b","c","d"))
#> [1] "a" "b" "c" "d"
```

The **dplyr** package includes a version of `union` that combines all the rows of two tables with the same column names.

```
tab_1 <- tab[1:5,]
tab_2 <- tab[3:7,]
dplyr::union(tab_1, tab_2)
#>         state abb    region population total ev clinton trump
#> 1     Alabama  AL     South    4779736   135  9    34.4  62.1
#> 2      Alaska  AK      West     710231    19  3    36.6  51.3
#> 3     Arizona  AZ      West    6392017   232 11    45.1  48.7
#> 4    Arkansas  AR     South    2915918    93  6    33.7  60.6
#> 5  California  CA      West   37253956  1257 55    61.7  31.6
#> 6    Colorado  CO      West    5029196    65  9    48.2  43.3
#> 7 Connecticut  CT Northeast    3574097    97  7    54.6  40.9
```

22.3.3 `setdiff`

The set difference between a first and second argument can be obtained with `setdiff`. Unlike `intersect` and `union`, this function is not symmetric:

```
setdiff(1:10, 6:15)
#> [1] 1 2 3 4 5
setdiff(6:15, 1:10)
#> [1] 11 12 13 14 15
```

As with the functions shown above, **dplyr** has a version for data frames:

```
tab_1 <- tab[1:5,]
tab_2 <- tab[3:7,]
dplyr::setdiff(tab_1, tab_2)
#>     state abb region population total ev clinton trump
#> 1 Alabama  AL  South    4779736   135  9    34.4  62.1
#> 2  Alaska  AK   West     710231    19  3    36.6  51.3
```

22.3.4 `setequal`

Finally, the function `setequal` tells us if two sets are the same, regardless of order. So notice that:

```
setequal(1:5, 1:6)
#> [1] FALSE
```

but:

```
setequal(1:5, 5:1)
#> [1] TRUE
```

When applied to data frames that are not equal, regardless of order, the **dplyr** version provides a useful message letting us know how the sets are different:

```
dplyr::setequal(tab_1, tab_2)
#> [1] FALSE
```

22.4 Exercises

1. Install and load the **Lahman** library. This database includes data related to baseball teams. It includes summary statistics about how the players performed on offense and defense for several years. It also includes personal information about the players.

The `Batting` data frame contains the offensive statistics for all players for many years. You can see, for example, the top 10 hitters by running this code:

```
library(Lahman)

top <- Batting %>%
  filter(yearID == 2016) %>%
  arrange(desc(HR)) %>%
  slice(1:10)

top %>% as_tibble()
```

But who are these players? We see an ID, but not the names. The player names are in this table

```
Master %>% as_tibble()
```

We can see column names `nameFirst` and `nameLast`. Use the `left_join` function to create a table of the top home run hitters. The table should have `playerID`, first name, last name, and number of home runs (HR). Rewrite the object `top` with this new table.

2. Now use the `Salaries` data frame to add each player's salary to the table you created in exercise 1. Note that salaries are different every year so make sure to filter for the year 2016, then use `right_join`. This time show first name, last name, team, HR, and salary.

3. In a previous exercise, we created a tidy version of the `co2` dataset:

```
co2_wide <- data.frame(matrix(co2, ncol = 12, byrow = TRUE)) %>%
  setNames(1:12) %>%
  mutate(year = 1959:1997) %>%
  gather(month, co2, -year, convert = TRUE)
```

We want to see if the monthly trend is changing so we are going to remove the year effects and then plot the results. We will first compute the year averages. Use the `group_by` and `summarize` to compute the average co2 for each year. Save in an object called `yearly_avg` .

4. Now use the `left_join` function to add the yearly average to the `co2_wide` dataset. Then compute the residuals: observed co2 measure - yearly average.

5. Make a plot of the seasonal trends by year but only after removing the year effect.

79. https://github.com/rstudio/cheatsheets↩

80. https://github.com/rstudio/cheatsheets/blob/master/LICENSE↩