15 How to expand data frames and create complete combinations of values

What will this tutorial cover?

In this tutorial you will find out how to create complete sets of values using `complete`, `expand` and `crossing`. I will try to show you how these functions differ and for which use cases they are useful.

Who do I have to thank?

For this tutorial, I relied on the official documentation. Kudos to the developers Hadley Wickham and Maximilian Girlich.

I've always found it difficult to distinguish the functions `complete`, `expand`, `nesting`, and `crossing` from another. In a sense, they do similar things. They find combinations of values in vectors or columns. I originally thought of writing a separate tutorial for each function, but digesting them all at once makes it easier to tell the difference between them. Let's take some time to look into these functions. And let's start with an overview of what they do:

Function	Explanation
complete	Turn implicit missing values into explicit values. The function completes combinations of values from columns that exist in a data frame and/or from vectors. `complete` is a shortcut version of `expand`.
expand	Creates a new tibble with all possible combinations of values from a data frame. The function is often used with joins.
expand with nesting	Create a new tibble with the unique combinations of column values that exist in a data frame.
crossing	Create a tibble with all combinations of values from vectors.

If you look at this table, you will notice a couple of things. First, `complete` makes an existing data frame longer by converting implicit values to existing values. This means that combinations of values that are not present in the data are created as new rows.

`expand`, in contrast, creates a new tibble. The tibble represents either all possible combinations of values or the unique combinations of values (with `nesting`). Suppose you have an incomplete tibble with months and years, in which the combination of the month "February" and the year 2013 is missing. You can use `expand` to create a complete set of years and months, including the combination of February and 2013. `crossing` works similarly to `expand`, except that it uses *vectors* to create combinations of values in a data frame. However, as we will see later, `expand` can also do this.

For this tutorial, we will use a made-up data set of running events. Suppose the following data frame shows the running races a runner has completed since 2010. The minutes show the time it took this person to complete the races. Let's call her Anna.

```
running_races_anna<- tribble(
  ~year, ~race,              ~minutes,
  2010,   "half marathon",   110,
  2011,   "marathon",        230,
  2013,   "half marathon",   105,
  2016,   "10km",            50,
  2018,   "10km",            45,
  2018,   "half marathon",   100,
  2022,   "marathon",        210
)
```

You can see that some years are missing. Anna didn't run a race in 2012. Also, she did not run a half marathon in 2016. In the next chapters, we will try to complete this data frame with the four functions. Let's start with `complete`.

15.1 `complete`

Let's assume Anna has only run 10Ks, half marathons, and marathons in recent years. Let's further assume that she could have participated in every race each year. How many running races could she have participated in then?

A first approach could be to convert the implicit combinations into explicit combinations using `complete`. This essentially means nothing more than creating new rows representing the runs in which it did not participate. For these runs, `complete` sets the values of the `minutes` column to `NA`:

```
running_races_anna %>%
  complete(year, race)
```

```
# A tibble: 18 x 3
    year race          minutes
   <dbl> <chr>           <dbl>
 1  2010 10km               NA
 2  2010 half marathon     110
 3  2010 marathon           NA
 4  2011 10km               NA
 5  2011 half marathon      NA
 6  2011 marathon          230
 7  2013 10km               NA
 8  2013 half marathon     105
 9  2013 marathon           NA
10  2016 10km               50
11  2016 half marathon      NA
12  2016 marathon           NA
13  2018 10km               45
14  2018 half marathon     100
15  2018 marathon           NA
16  2022 10km               NA
17  2022 half marathon      NA
18  2022 marathon          210
```

Looking at the number of rows she could have participated in 18 competitions. But could she? You might see that we are missing some years. There is no data from 2012 or 2014. This is because `complete` only works with the values that are already in the data. Since she never participated in a race in 2012, we don't see these races.

However, we can add these values if we use vectors instead of columns. Suppose we want to ensure that the data frame includes all years between 2010 and 2022 and all three running events that are already present in the data:

```r
running_races_anna %>%
  complete(year = 2010:2022, race)
```

```
# A tibble: 39 x 3
    year race          minutes
   <dbl> <chr>           <dbl>
 1  2010 10km               NA
 2  2010 half marathon     110
 3  2010 marathon           NA
 4  2011 10km               NA
 5  2011 half marathon      NA
```

```
 6  2011 marathon          230
 7  2012 10km               NA
 8  2012 half marathon      NA
 9  2012 marathon           NA
10  2013 10km               NA
# ... with 29 more rows
```

All combinations of values that were already present in the data did not change. However, the code added rows that were not present. In other words, it added rows with years and races that were not present in the original data frame.

We could even go so far as to include new races to the data frame (i.e. ultra marathons):

```r
running_races_anna %>%
  complete(year = 2010:2022, race = c(race, "ultra marathons"))
```

```
# A tibble: 52 x 3
    year race            minutes
   <dbl> <chr>             <dbl>
 1  2010 10km                 NA
 2  2010 half marathon       110
 3  2010 marathon             NA
 4  2010 ultra marathons      NA
 5  2011 10km                 NA
 6  2011 half marathon        NA
 7  2011 marathon            230
 8  2011 ultra marathons      NA
 9  2012 10km                 NA
10  2012 half marathon        NA
# ... with 42 more rows
```

Look how we created a vector that includes the races already present in the data plus ultra marathons.

15.2 `expand`

The `expand` function does something very similar. However, instead of adding new rows with the complete set of values, a new data frame is created only for the columns you specify in the function (compared to `complete`, where we kept the `minutes` column).

First, let's create a simple example. Let's create a complete combination of years and races from the existing data frame:

```r
running_races_anna %>%
  expand(year, race)
```

```
# A tibble: 18 x 2
    year race
   <dbl> <chr>
 1  2010 10km
 2  2010 half marathon
 3  2010 marathon
 4  2011 10km
 5  2011 half marathon
 6  2011 marathon
 7  2013 10km
 8  2013 half marathon
 9  2013 marathon
10  2016 10km
11  2016 half marathon
12  2016 marathon
13  2018 10km
14  2018 half marathon
15  2018 marathon
16  2022 10km
17  2022 half marathon
18  2022 marathon
```

The result is a new data frame. You can see that the column `minutes` is missing. Similar to `complete` we can specify a vector instead of a column, for example to make sure that the data frame covers all years from 2010 to 2022:

```r
running_races_anna %>%
  expand(year = 2010:2022, race)
```

```
# A tibble: 39 x 2
    year race
   <int> <chr>
 1  2010 10km
 2  2010 half marathon
 3  2010 marathon
```

```
 4  2011 10km
 5  2011 half marathon
 6  2011 marathon
 7  2012 10km
 8  2012 half marathon
 9  2012 marathon
10  2013 10km
# ... with 29 more rows
```

A neat trick to complete the years is the `full_seq` function:

```r
running_races_anna %>%
  expand(year = full_seq(year, 1), race)
```

```
# A tibble: 39 x 2
    year race
   <dbl> <chr>
 1  2010 10km
 2  2010 half marathon
 3  2010 marathon
 4  2011 10km
 5  2011 half marathon
 6  2011 marathon
 7  2012 10km
 8  2012 half marathon
 9  2012 marathon
10  2013 10km
# ... with 29 more rows
```

In this case `full_seq` generated the complete set of years, starting with the lowest year in the data frame and ending with the highest year. The `1` indicates that the years should be incremented by 1 each time.

So we have a handle on all the combinations of years and races in our data frame. But we are missing the actual data, namely the minutes Anna took for these races. To add this data to the data frame, we combine `expand` with `full_join`:

```r
(all_running_races_anna <- running_races_anna %>%
  expand(year = full_seq(year, 1), race) %>%
  full_join(running_races_anna, by = c("year", "race")))
```

```
# A tibble: 39 x 3
    year race          minutes
   <dbl> <chr>           <dbl>
 1  2010 10km               NA
 2  2010 half marathon     110
 3  2010 marathon           NA
 4  2011 10km               NA
 5  2011 half marathon      NA
 6  2011 marathon          230
 7  2012 10km               NA
 8  2012 half marathon      NA
 9  2012 marathon           NA
10  2013 10km               NA
# ... with 29 more rows
```

This data frame includes all 39 races that Anna could have participated in between 2010 and 2022.

You may wonder why you should use `expand` instead of `complete` at all? The result is the same we got with `complete`. And the code it is more complicated.

If you take a look at the document, you will see that `complete` is actually a wrapper around `expand`. In other words, it is `expand` combined with `full_join` (see the official code on GitHub). Essentially, it is a shortcut for the more complicated code we just used. We will show this in the upcoming examples.

15.3 `expand/complete` with `group_by`

Now let's imagine Anna is running in a club with three other runners. Eva, John and Leonie.

```
running_races_club <- tribble(
  ~year, ~runner,   ~race,             ~minutes,
  2012,  "Eva",     "half marathon",   109,
  2013,  "Eva",     "marathon",        260,
  2022,  "Eva",     "half marathon",   120,
  2018,  "John",    "10km",            51,
  2019,  "John",    "10km",            49,
  2020,  "John",    "10km",            50,
  2019,  "Leonie",  "half marathon",   45,
  2020,  "Leonie",  "10km",            45,
  2021,  "Leonie",  "half marathon",   102,
  2022,  "Leonie",  "marathon",        220
```

```
)
```

Again, you want to find all races that each runner could have participated in since joining the club. If we used the same `expand` technique we just did, we will run into problems:

```
(all_running_races_club <- running_races_club %>%
  expand(year = full_seq(year, 1), race,  runner))
```

```
# A tibble: 99 x 3
    year race          runner
   <dbl> <chr>         <chr>
 1  2012 10km          Eva
 2  2012 10km          John
 3  2012 10km          Leonie
 4  2012 half marathon Eva
 5  2012 half marathon John
 6  2012 half marathon Leonie
 7  2012 marathon      Eva
 8  2012 marathon      John
 9  2012 marathon      Leonie
10  2013 10km          Eva
# ... with 89 more rows
```

Take John, for example:

```
all_running_races_club %>%
  filter(runner == "John")
```

```
# A tibble: 33 x 3
    year race          runner
   <dbl> <chr>         <chr>
 1  2012 10km          John
 2  2012 half marathon John
 3  2012 marathon      John
 4  2013 10km          John
 5  2013 half marathon John
 6  2013 marathon      John
 7  2014 10km          John
 8  2014 half marathon John
 9  2014 marathon      John
10  2015 10km          John
```

```
# ... with 23 more rows
```

He joined the club in 2019. However, the data frame shows missed races from 2012. This is because the data frame contains the races of Eva, who joined in 2012.

We can fix this problem by grouping the data frame by runners.

```r
(all_running_races_club_correct <- running_races_club %>%
  group_by(runner) %>%
  expand(year = full_seq(year, 1), race = c("10km", "half marathon",
                                             "marathon")) %>%
  ungroup())
```

```
# A tibble: 54 x 3
   runner  year race
   <chr>  <dbl> <chr>
 1 Eva     2012 10km
 2 Eva     2012 half marathon
 3 Eva     2012 marathon
 4 Eva     2013 10km
 5 Eva     2013 half marathon
 6 Eva     2013 marathon
 7 Eva     2014 10km
 8 Eva     2014 half marathon
 9 Eva     2014 marathon
10 Eva     2015 10km
# ... with 44 more rows
```

With `group_by` we expand the rows only within the runners. If you now take a look at the data, you will notice that John has no races before 2018, which is exactly what we want.

```r
all_running_races_club_correct %>%
  filter(runner == "John")
```

```
# A tibble: 9 x 3
  runner  year race
  <chr>  <dbl> <chr>
1 John    2018 10km
2 John    2018 half marathon
3 John    2018 marathon
4 John    2019 10km
```

```
5 John     2019 half marathon
6 John     2019 marathon
7 John     2020 10km
8 John     2020 half marathon
9 John     2020 marathon
```

Yet, we still need the actual data of the three runners. We use `left_join` to add the running times to the expanded data frame:

```r
(complete_running_races_club <- all_running_races_club_correct %>%
  left_join(running_races_club, by = c("year", "runner", "race")))
```

```
# A tibble: 54 x 4
   runner  year race          minutes
   <chr>  <dbl> <chr>           <dbl>
 1 Eva     2012 10km               NA
 2 Eva     2012 half marathon     109
 3 Eva     2012 marathon           NA
 4 Eva     2013 10km               NA
 5 Eva     2013 half marathon      NA
 6 Eva     2013 marathon          260
 7 Eva     2014 10km               NA
 8 Eva     2014 half marathon      NA
 9 Eva     2014 marathon           NA
10 Eva     2015 10km               NA
# ... with 44 more rows
```

Since we already know that `complete` is a shortcut for such an analysis, we can use it instead:

```r
running_races_club %>%
  group_by(runner) %>%
  complete(year = full_seq(year, 1), race = c("10km", "half marathon",
                                              "marathon")) %>%

  ungroup()
```

```
# A tibble: 54 x 4
   runner  year race          minutes
   <chr>  <dbl> <chr>           <dbl>
 1 Eva     2012 10km               NA
 2 Eva     2012 half marathon     109
```

```
 3 Eva     2012 marathon           NA
 4 Eva     2013 10km               NA
 5 Eva     2013 half marathon      NA
 6 Eva     2013 marathon          260
 7 Eva     2014 10km               NA
 8 Eva     2014 half marathon      NA
 9 Eva     2014 marathon           NA
10 Eva     2015 10km               NA
# ... with 44 more rows
```

With this data we can do some interesting analysis. We could visualize the percentage of competitions in which each runner actually participated.

First, we need to find out how many races each runner has completed. To do this, we count the number of races that a runner has or has not completed:

```r
(count_races <- complete_running_races_club %>%
  count(runner, race, missed_races = is.na(minutes)))
```

```
# A tibble: 14 x 4
   runner race          missed_races     n
   <chr>  <chr>         <lgl>        <int>
 1 Eva    10km          TRUE            11
 2 Eva    half marathon FALSE            2
 3 Eva    half marathon TRUE             9
 4 Eva    marathon      FALSE            1
 5 Eva    marathon      TRUE            10
 6 John   10km          FALSE            3
 7 John   half marathon TRUE             3
 8 John   marathon      TRUE             3
 9 Leonie 10km          FALSE            1
10 Leonie 10km          TRUE             3
11 Leonie half marathon FALSE            2
12 Leonie half marathon TRUE             2
13 Leonie marathon      FALSE            1
14 Leonie marathon      TRUE             3
```

We see that Eva has not completed a single 10-km run in the years she has been a member of the club, because there is a row missing where the `missed_races` column is set to `FALSE`.

Fortunately, we have learned that we can complete an existing data frame with `complete`. Let's do that:

```r
count_races %>%
  complete(runner, race, missed_races, fill = list(n = 0))
```

```
# A tibble: 18 x 4
   runner race          missed_races     n
   <chr>  <chr>         <lgl>        <int>
 1 Eva    10km          FALSE            0
 2 Eva    10km          TRUE            11
 3 Eva    half marathon FALSE            2
 4 Eva    half marathon TRUE             9
 5 Eva    marathon      FALSE            1
 6 Eva    marathon      TRUE            10
 7 John   10km          FALSE            3
 8 John   10km          TRUE             0
 9 John   half marathon FALSE            0
10 John   half marathon TRUE             3
11 John   marathon      FALSE            0
12 John   marathon      TRUE             3
13 Leonie 10km          FALSE            1
14 Leonie 10km          TRUE             3
15 Leonie half marathon FALSE            2
16 Leonie half marathon TRUE             2
17 Leonie marathon      FALSE            1
18 Leonie marathon      TRUE             3
```

The code has an interesting addition, the `fill` parameter. The parameter allows us turn `NA`s to actual values. Since we know that the missing rows represent the number of races that were or were not finish, we can be sure that they represent zero races. For Eva, for example, a row is missing for the 10km races in which she never participated.

Now that we have the complete count data of races per runner, we can calculate the percentage of races they participated in. To calculate the percentages, we must first put the data into a wide format and then create a column that represents the percentages:

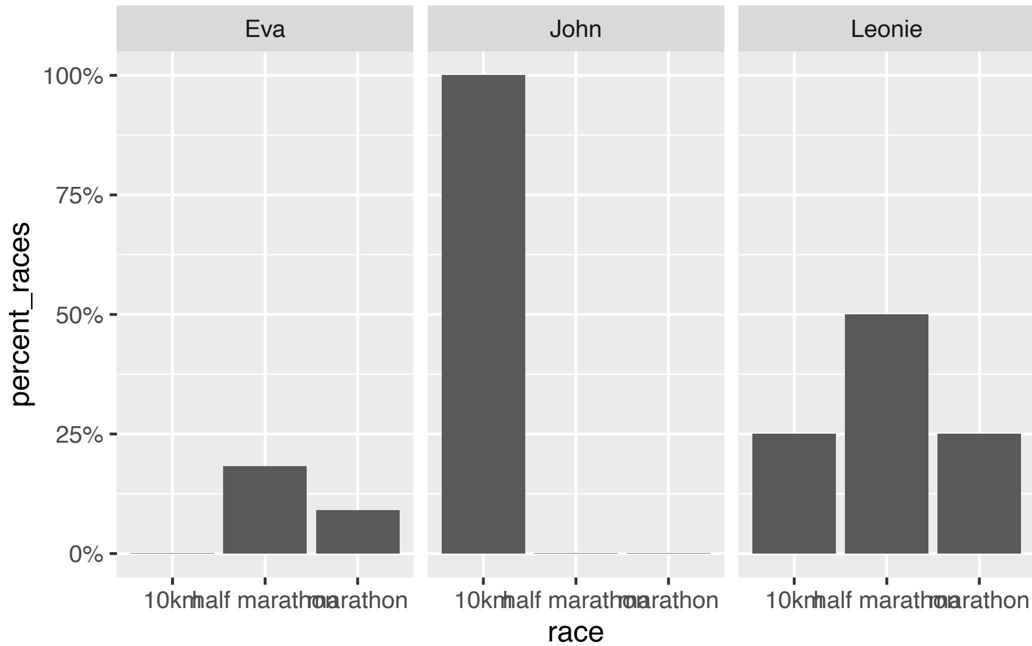
```r
count_races %>%
  complete(runner, race, missed_races, fill = list(n = 0)) %>%
  pivot_wider(names_from = missed_races, values_from = n) %>%
  mutate(
    percent_races =  (`FALSE` /  (`TRUE` + `FALSE`)) * 100
  )
```

```
# A tibble: 9 x 5
  runner race          `FALSE` `TRUE` percent_races
  <chr>  <chr>           <int>  <int>         <dbl>
1 Eva    10km                0     11          0
2 Eva    half marathon       2      9         18.2
3 Eva    marathon            1     10          9.09
4 John   10km                3      0        100
5 John   half marathon       0      3          0
6 John   marathon            0      3          0
7 Leonie 10km                1      3         25
8 Leonie half marathon       2      2         50
9 Leonie marathon            1      3         25
```

Let's talk about Eva again. She participated in 0% of the 10k races and in 18.18% of the possible half marathons. Since she ran only 1 of 11 marathons, she participated in 9% of the marathons.

This is how it looks for all runners:

```
count_races %>%
  complete(runner, race, missed_races, fill = list(n = 0)) %>%
  pivot_wider(names_from = missed_races, values_from = n) %>%
  mutate(
    percent_races =  (`FALSE` /  (`TRUE` + `FALSE`)) * 100
  ) %>%
  ggplot(aes(x = race, y = percent_races)) +
  scale_y_continuous(labels = scales::label_percent(scale = 1)) +
  geom_col() +
  facet_wrap(vars(runner))
```



15.4 `expand` with `nesting`

So far, we have completed data frames for missing rows. Sometimes, however, we are interested in the unique combinations of values in a data frame. Suppose your running club has 540 members. You want to know in which competitions a runner has participated during her or his time in the club. This is basically the opposite of what we just did. Instead of finding all combinations of values we are looking for the unique combinations; in a given data frame!

To find these combinations we can combine `expand` with `nesting`:

```
running_races_club %>%
  expand(nesting(runner, race))
```

```
# A tibble: 6 x 2
  runner race
  <chr>  <chr>
1 Eva    half marathon
2 Eva    marathon
3 John   10km
4 Leonie 10km
5 Leonie half marathon
```

```
6 Leonie marathon
```

Once again, you can see that Eva has never run a 10K. John has never run a half marathon or marathon. But we have to infer that information from the data frame. The data shows what happened, not what didn't happen. To find out which runs the runners have never participated in, we can combine the code with `anti_join`:

```
full_combinations_runners <- expand(running_races_club,
       runner, race = c("10km", "half marathon","marathon"))

full_combinations_runners %>%
  anti_join(running_races_club, by = c("runner", "race"))
```

```
# A tibble: 3 x 2
  runner race
  <chr>  <chr>
1 Eva    10km
2 John   half marathon
3 John   marathon
```

The result of our analysis is now easier to process, as we no longer have to search for the known unknowns and get the desired results directly.

15.5 `crossing`

Let's talk about tennis. Suppose you want to create a data frame that shows all Grand Slams (Australian Open, French Open, Wimbledon, US Open) from 1905 to 2022 (1905 was the first year all Grand Slams were held). You don't have an existing data frame at hand, so you need to create one from scratch.

For these cases you need `crossing`. The difference from the other functions is that `crossing` does not need an existing data frame. We use vectors instead:

```
crossing(
  year = 1905:2022,
  major = c("Australien Open", "French Open",
            "Wimbledon", "US Open")
)
```

```
# A tibble: 472 x 2
    year major
   <int> <chr>
 1  1905 Australien Open
 2  1905 French Open
 3  1905 US Open
 4  1905 Wimbledon
 5  1906 Australien Open
 6  1906 French Open
 7  1906 US Open
 8  1906 Wimbledon
 9  1907 Australien Open
10  1907 French Open
# ... with 462 more rows
```

This gives us a total of 472 Grand Slams.

Similarly, we could create a data frame representing the World Marathon Majors, which started in 2006:

```r
crossing(
  year = 2006:2022,
  races = c("Tokyo", "Boston", "Chicago",
            "London", "Berlin", "New York")
)
```

```
# A tibble: 102 x 2
    year races
   <int> <chr>
 1  2006 Berlin
 2  2006 Boston
 3  2006 Chicago
 4  2006 London
 5  2006 New York
 6  2006 Tokyo
 7  2007 Berlin
 8  2007 Boston
 9  2007 Chicago
10  2007 London
# ... with 92 more rows
```

The data itself only gives us a complete set of combinations, by itself it is not very meaningful. `crossing` is usually a starting point for further analyses. Imagine if we had a data set with all the world records set at these majors. We could join the world records to this data frame to determine the percentage of races in which a world record was set at the six majors.

> **Summary**
>
> - `complete`, `expand` and `crossing` all create complete sets of combinations of values. `complete` and `expand` derive the complete set from values already present in a data frame or vectors, `crossing` from vectors only.
> - `complete` is a wrapper around `expand`. It is basically `expand` in combination with `full_join`
> - `complete` and `expand` can be used for grouped data frames to complete a set of combinations of values within groups only.
> - `expand` and `crossing` create a new data frame, `complete` adds rows to an existing data frame
> - `expand` in combination with `nesting` gives you the unique combinations of values in a data frame.