12 - Tidy Data

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Contents

1 Tidy Data **2**
1.1 Get the Rate (cases/population) 2
1.2 Why Tidy Data? 4

2 Main `tidyr` functions **4**
2.1 `gather()` into long form 5
2.2 `spread()` into wide form 6
2.3 `separate()` 8
2.4 `unite()` 10

3 Missing Data **11**
3.1 Missing Values 11

4 Your Turn **12**
4.1 Problem 1: Tornado 12
4.2 Problem 2: Time of Day 13
4.3 Problem 3: Pew Survey 13

5 Other functions in `tidyr` package **13**

Required Packages and Data

```
library(tidyverse)
```

1 Tidy Data

The textbook has some examples of tidy and untidy data

```
library(tidyverse)
data(package="tidyr")
# table1, table2, table3, table4a, table4b
```

1.1 Get the Rate (cases/population)

For each table, calculate the `rate = cases/population`.

1.1.1 Table 1

```
table1
#> # A tibble: 6 × 4
#>       country  year  cases population
#>         <chr> <int>  <int>      <int>
#> 1 Afghanistan  1999    745   19987071
#> 2 Afghanistan  2000   2666   20595360
#> 3      Brazil  1999  37737  172006362
#> 4      Brazil  2000  80488  174504898
#> 5       China  1999 212258 1272915272
#> 6       China  2000 213766 1280428583
```

Your Turn #1

What `dplyr` function can be used to create the `rate` column?

1.1.2 Table 2

```
table2
#> # A tibble: 12 × 4
#>        country  year       type      count
#>          <chr> <int>      <chr>      <int>
#> 1  Afghanistan  1999      cases        745
#> 2  Afghanistan  1999 population   19987071
#> 3  Afghanistan  2000      cases       2666
#> 4  Afghanistan  2000 population   20595360
#> 5       Brazil  1999      cases      37737
#> 6       Brazil  1999 population  172006362
#> 7       Brazil  2000      cases      80488
#> 8       Brazil  2000 population  174504898
#> 9        China  1999      cases     212258
#> 10       China  1999 population 1272915272
#> 11       China  2000      cases     213766
#> 12       China  2000 population 1280428583
```

Your Turn #2

What needs to be done to calculate the rate?
Hint: what constitutes an *observation*, and what are the *variables*? Another way to consider is by identifying the *primary key(s)* of the table.

1.1.3 Table 3

```
table3
#> # A tibble: 6 × 3
#>       country  year              rate
#> *       <chr> <int>             <chr>
#> 1 Afghanistan  1999      745/19987071
#> 2 Afghanistan  2000     2666/20595360
#> 3      Brazil  1999   37737/172006362
#> 4      Brazil  2000   80488/174504898
#> 5       China  1999 212258/1272915272
#> 6       China  2000 213766/1280428583
```

Your Turn #3

What needs to be done to actually calculate the rate?

1.1.4 Tables 4a and 4b

```
table4a
#> # A tibble: 3 × 3
#>       country `1999` `2000`
#> *       <chr>  <int>  <int>
#> 1 Afghanistan    745   2666
#> 2      Brazil  37737  80488
#> 3       China 212258 213766
table4b
#> # A tibble: 3 × 3
#>       country     `1999`     `2000`
#> *       <chr>      <int>      <int>
#> 1 Afghanistan   19987071   20595360
#> 2      Brazil  172006362  174504898
#> 3       China 1272915272 1280428583
```

Your Turn #4

What needs to be done to calculate the rate?
Hint: The info is split between two tables. Would it help if each table was in a different form?

1.2 Why Tidy Data?

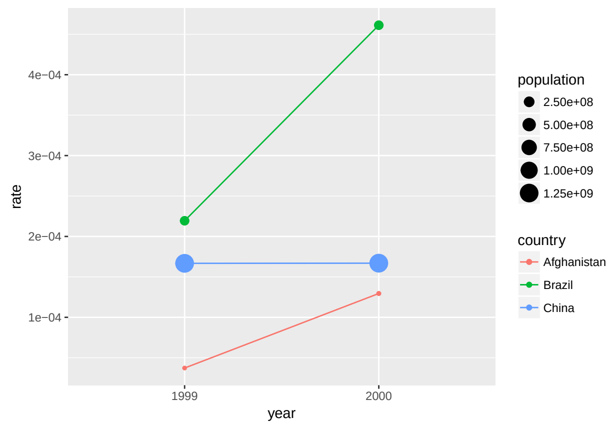
- Tidy data (in form of a data frame) is usually the best form for analysis
  - some exceptions are for modeling (e.g., matrix manipulations and algorithms)
- For presentation of data (e.g., in tables), non-tidy form can often do better
- the functions in `tidyr` usually allow us to covert from non-tidy to tidy for analysis and also from tidy to non-tidy for presentation

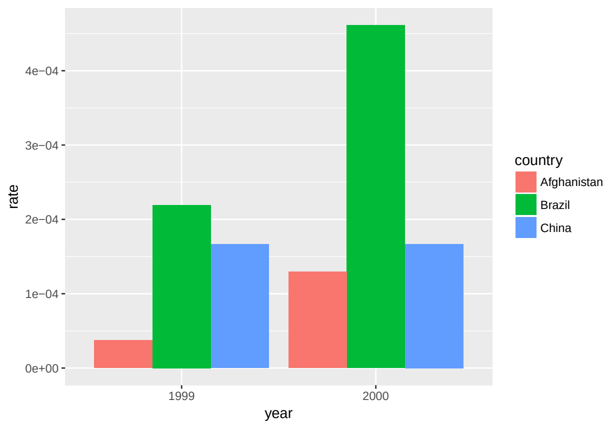
2 Main `tidyr` functions

function	description
`spread()`	Spreads a pair of key:value columns into a set of tidy columns
`gather()`	Gather takes multiple columns and collapses into key-value pairs, duplicating all other columns as needed. You use gather() when you notice that you have columns that are not variables
`separate()`	turns a single character column into multiple columns
`unite()`	paste together multiple columns into one (reverse of `separate()`)

Tidy data is often the form we want for further analysis. For example, here are some basic plots that would be difficult to make in the untidy versions.

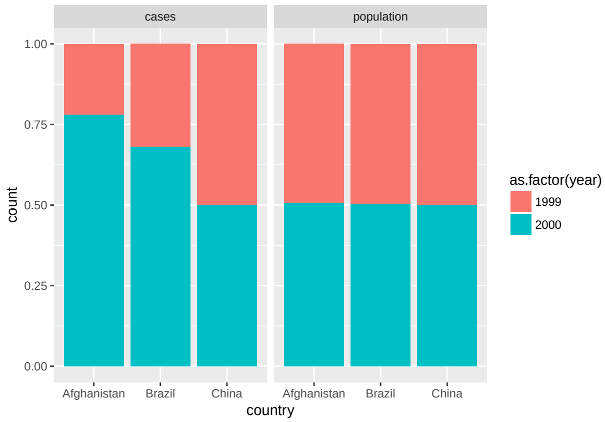
```
tidy_table = table1 %>% mutate(rate=cases/population)

#- line plot
ggplot(tidy_table, aes(x=as.factor(year), y=rate, color=country, group=country)) +
  geom_line() + geom_point(aes(size=population)) + xlab("year")

#- bar plot
ggplot(tidy_table, aes(x=as.factor(year), y=rate, fill=country)) +
  geom_bar(stat="identity", position="dodge") + xlab("year")
```





One exception is if we want to facet (or group) by `type` column(s). Then `table2` is better.

```
ggplot(table2, aes(x=country, y=count, fill=as.factor(year))) +
  geom_bar(stat="identity", position="fill") + facet_wrap(~type)
```



The `tidyr` package provides functionality to convert to and from tidy data, which can greatly speed up analysis and help structure your thinking.

2.1 `gather()` into long form

The `gather()` function collects a set of column names and places them into a single "key" column. It also collects the field of cells associated with those columns and places them into a single value column.

In the example from 12.3.1 R4DS, `table4a` (cases) and `table4b` (population) are gathered into two columns: year and value.

```
table4a
#> # A tibble: 3 × 3
#>       country `1999` `2000`
#> *       <chr>  <int>  <int>
#> 1 Afghanistan    745   2666
#> 2      Brazil  37737  80488
#> 3       China 212258 213766
(tidy4a = gather(table4a, key="year", value="cases", 2:3))
#> # A tibble: 6 × 3
#>       country  year  cases
#>         <chr> <chr>  <int>
#> 1 Afghanistan  1999    745
#> 2      Brazil  1999  37737
#> 3       China  1999 212258
#> 4 Afghanistan  2000   2666
#> 5      Brazil  2000  80488
#> 6       China  2000 213766
```

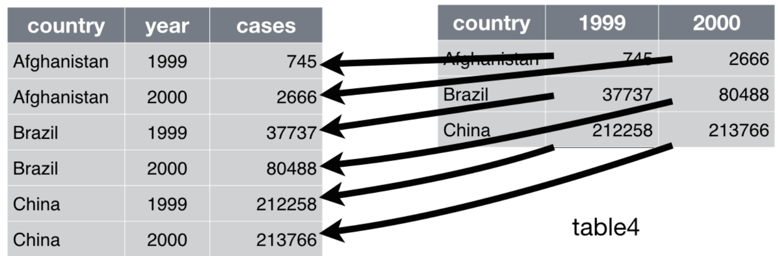


Figure 1: Gathering `table4` into a tidy form.

The function is:

```
gather(
    data = <data frame>,
    key = <name of new key column>,
    value = <name of new value column>,
    ... = <specification of columns to gather>,
    <optional.args>)
```

where the specification of columns could be by name, index, or any method allowed by the `?dplyr::select()` function.

Your Turn #5

1. For tidying table4, how were the columns to gather specified?
2. What would be an alternative way to specify them?
3. Tidy up table4b.
4. Calculate the disease rate.

2.2 `spread()` into wide form

The `spread()` function is the opposite of `gather()` and converts two columns (one key, one value) into a set of columns (one new column for every unique key value).

The `table2` can be *spread* into a tidy format

```
table2
#> # A tibble: 12 × 4
#>        country  year       type      count
#>          <chr> <int>      <chr>      <int>
#> 1  Afghanistan  1999      cases        745
#> 2  Afghanistan  1999 population   19987071
#> 3  Afghanistan  2000      cases       2666
#> 4  Afghanistan  2000 population   20595360
#> 5       Brazil  1999      cases      37737
#> 6       Brazil  1999 population  172006362
```

```
#> 7        Brazil  2000       cases       80488
#> 8        Brazil  2000 population  174504898
#> 9         China  1999       cases      212258
#> 10        China  1999 population 1272915272
#> 11        China  2000       cases      213766
#> 12        China  2000 population 1280428583
unique(table2$type)
#> [1] "cases"      "population"
spread(table2, key=type, value=count)
#> # A tibble: 6 × 4
#>       country  year  cases population
#> *       <chr> <int>  <int>      <int>
#> 1 Afghanistan  1999    745   19987071
#> 2 Afghanistan  2000   2666   20595360
#> 3      Brazil  1999  37737  172006362
#> 4      Brazil  2000  80488  174504898
#> 5       China  1999 212258 1272915272
#> 6       China  2000 213766 1280428583
```

Notice that 2 extra columns were added (`cases` and `population`) according the unique values in `type`.

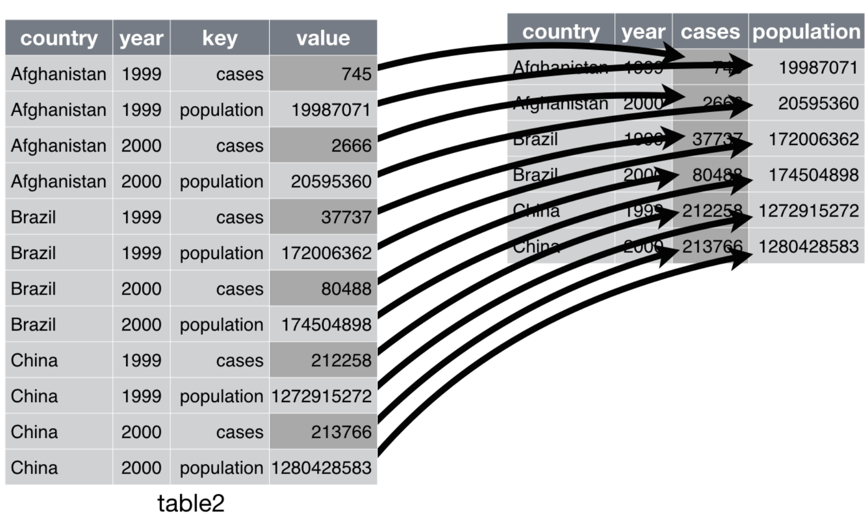


Figure 2: Spreading `table2` makes it tidy.

The function is:

```
spread(
   data = <data frame>,
   key = <unquoted name of key column>,
   value = <unquoted name of value column>,
   fill = <the value to replace NA's>,
   convert = <logical. Convert (parse) the new columns.>
   <optional.args>)
```

2.3 separate()

The `separate()` function pulls apart one column into multiple columns, by splitting wherever the separator (`sep=`) character appears.

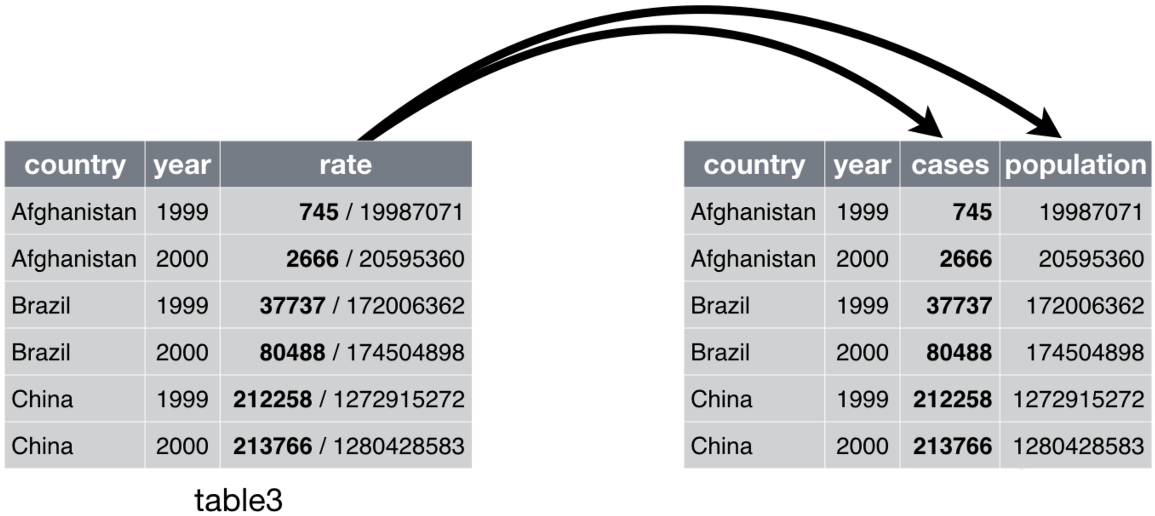
In `table3`, the *equation* for the rate is given, but not the calculated value. One approach is to use the `separate()` function from `tidyr` to separate this one column into two which gives us `table1`.

```
table3
#> # A tibble: 6 × 3
#>       country  year              rate
#> *       <chr> <int>             <chr>
#> 1 Afghanistan  1999      745/19987071
#> 2 Afghanistan  2000     2666/20595360
#> 3      Brazil  1999   37737/172006362
#> 4      Brazil  2000   80488/174504898
#> 5       China  1999 212258/1272915272
#> 6       China  2000 213766/1280428583
separate(table3, rate, into=c("cases", "population"), sep="/", convert=TRUE) %>%
  mutate(rate=cases/population)
#> # A tibble: 6 × 5
#>       country  year  cases population      rate
#>         <chr> <int>  <int>      <int>     <dbl>
#> 1 Afghanistan  1999    745   19987071 3.727e-05
#> 2 Afghanistan  2000   2666   20595360 1.294e-04
#> 3      Brazil  1999  37737  172006362 2.194e-04
#> 4      Brazil  2000  80488  174504898 4.612e-04
#> 5       China  1999 212258 1272915272 1.667e-04
#> 6       China  2000 213766 1280428583 1.669e-04
```

Notice that we used the optional arguments `sep="/"` and `convert=TRUE`.

```
separate(
   data = <data frame>,
   col = <unquoted name column to separate>,
   into = <names of new columns (character vector)>,
   sep = <the separator>,
   remove = <logical. remove original column?>
   convert = <logical. Convert (parse) the new columns.>
   <optional.args>)
```

The `separate()` functions is also useful for extracting date and time elements.



country	year	rate
Afghanistan	1999	**745** / 19987071
Afghanistan	2000	**2666** / 20595360
Brazil	1999	**37737** / 172006362
Brazil	2000	**80488** / 174504898
China	1999	**212258** / 1272915272
China	2000	**213766** / 1280428583

table3

country	year	cases	population
Afghanistan	1999	**745**	19987071
Afghanistan	2000	**2666**	20595360
Brazil	1999	**37737**	172006362
Brazil	2000	**80488**	174504898
China	1999	**212258**	1272915272
China	2000	**213766**	1280428583

Figure 3: Separating `table3` makes it tidy.

Consider the following data that has date and event information.

```
url = "https://raw.githubusercontent.com/mdporter/ST597/master/data/date-event.csv"
(df = read_csv(url))
#> Parsed with column specification:
#> cols(
#>   date = col_date(format = ""),
#>   event = col_character()
#> )
#> # A tibble: 100 × 2
#>          date event
#>        <date> <chr>
#> 1  2016-01-16     D
#> 2  2016-03-29     D
#> 3  2016-01-17     B
#> 4  2016-05-16     A
#> 5  2016-04-13     C
#> 6  2016-03-29     B
#> 7  2016-01-14     A
#> 8  2016-01-25     C
#> 9  2016-04-18     D
#> 10 2016-01-25     A
#> # ... with 90 more rows
```

We want to know the distribution of event type by *day of the month*. One way to get this information is with the `separate()` function. The `separate()` function will split up a character column, according to some pattern, into multiple new columns. It essentially does a `str_split` and then adds the new columns into the data frame.

Here is the result with default settings

```
separate(df, col=date, into=c("year", "month", "day"), sep="-")
#> # A tibble: 100 × 4
#>      year month   day event
#> *   <chr> <chr> <chr> <chr>
#> 1    2016    01    16     D
#> 2    2016    03    29     D
#> 3    2016    01    17     B
#> 4    2016    05    16     A
#> 5    2016    04    13     C
#> 6    2016    03    29     B
#> 7    2016    01    14     A
#> 8    2016    01    25     C
#> 9    2016    04    18     D
#> 10   2016    01    25     A
#> # ... with 90 more rows
```

Notice a few things:

- The original `date` column was removed. We can keep it in with the argument `remove=FALSE`
- The new columns are still *character* vectors. If we want them to be numeric, we can set `convert=TRUE`, which attempt to convert the columns to the appropriate type.

This produces the following:

```
separate(df, col=date, into=c("year", "month", "day"), sep="-",
         remove=FALSE, convert=TRUE)
```

If we want counts per day:

```
df %>%
separate(col=date, into=c("year", "month", "day"), sep="-") %>%
  count(day, event)
```

Now use `spread()` to get into table form for easier display:

```
df %>%
separate(col=date, into=c("year", "month", "day"), sep="-",
         remove=FALSE, convert=TRUE) %>%
  count(day, event) %>%
  spread(key=event, value=n, fill=0)
```

2.4 `unite()`

The `unite()` function is the opposite of `separate()` and will recombine multiple columns.

```
df %>%
separate(col=date, into=c("year", "month", "day"), sep="-",
         remove=FALSE, convert=TRUE) %>%
  unite(col="USdate", month, day, year, sep="/")
#> # A tibble: 100 × 3
#>            date    USdate event
#> *        <date>     <chr> <chr>
#> 1   2016-01-16 1/16/2016     D
#> 2   2016-03-29 3/29/2016     D
```

```
#> 3  2016-01-17 1/17/2016     B
#> 4  2016-05-16 5/16/2016     A
#> 5  2016-04-13 4/13/2016     C
#> 6  2016-03-29 3/29/2016     B
#> 7  2016-01-14 1/14/2016     A
#> 8  2016-01-25 1/25/2016     C
#> 9  2016-04-18 4/18/2016     D
#> 10 2016-01-25 1/25/2016     A
#> # ... with 90 more rows
```

3 Missing Data

3.1 Missing Values

Changing the representation of a dataset brings up an important subtlety of missing values. Surprisingly, a value can be missing in one of two possible ways:

- *Explicitly*, i.e. flagged with `NA`.
- *Implicitly*, i.e. simply not present in the data.

In the previous example, there is some implicit missing data. What is missing, and what should be the value of the missing data?

```
df %>%
separate(col=date, into=c("year", "month", "day"), sep="-",
         remove=FALSE, convert=TRUE) %>%
  count(day, event) %>% arrange(day, event)
#> Source: local data frame [66 x 3]
#> Groups: day [29]
#>
#>      day event     n
#>    <int> <chr> <int>
#> 1      1     A     2
#> 2      1     D     2
#> 3      2     A     1
#> 4      2     B     2
#> 5      2     D     1
#> 6      4     C     1
#> 7      4     D     1
#> 8      5     D     2
#> 9      6     B     2
#> 10     6     C     1
#> # ... with 56 more rows
```

Now to fill in missing days with `complete()`

```
df %>%
separate(col=date, into=c("year", "month", "day"), sep="-",
         remove=FALSE, convert=TRUE) %>%
  count(day, event) %>%
  complete(day=1:31, event=c('A','B', 'C', 'D'), fill=list(n=0L))
#> Source: local data frame [3,596 x 3]
```

```
#> Groups: day [31]
#>
#>       day event     n
#>     <int> <chr> <int>
#> 1       1     A     2
#> 2       1     B     0
#> 3       1     C     0
#> 4       1     D     2
#> 5       2     A     1
#> 6       2     B     2
#> 7       2     C     0
#> 8       2     D     1
#> 9       3     A     0
#> 10      3     B     0
#> # ... with 3,586 more rows
```

3.1.1 Functions to know

- `complete()`
- `fill()`

4 Your Turn

4.1 Problem 1: Tornado

Your Turn #6 : Tidy Tornadoes

The US Storm Prediction Center make severe weather data available from the website http://www.spc.noaa.gov/wcm/#data. This data is used by insurance companies to help with their claims evalutation and forecasting. A description of the data can be found http://www.spc.noaa.gov/wcm/data/SPC_severe_database_description.pdf.
Use the tornado event data (https://raw.githubusercontent.com/mdporter/ST597/master/data/tornado.csv), to calculate the number of tornadoes by *year* and *Fujita score* (`f`) and then use `spread()` to convert the results to a table. The final result should look like this

yr	F0	F1	F2	F3	F4	F5
2007	681	306	97	27	4	1
2008	997	515	158	56	11	1
2009	709	355	94	21	3	0
2010	776	351	129	42	17	0
2011	821	638	212	72	25	9
2012	577	242	100	32	5	0
2013	508	314	86	22	8	1
2014	478	325	76	20	7	0
2015	704	415	69	19	5	0

a. Import the tornado data from https://raw.githubusercontent.com/mdporter/ST597/master/data/tornado.csv.
b. Create a data frame with columns year (`yr`), Fujita score (`f`), and count (`n`).
c. Use `spread()` to convert to the required (untidy) table. Note: Some years have 0 EF-5 tornadoes.

4.2 Problem 2: Time of Day

Your Turn #7 : Time-of-Day

The goal of this task is to plot the estimated density of the time when tornadoes occur. The `time` column in the `tornado` data gives the time-of-day (24 hour clock, central time zone) when the tornado occurred. Ignoring the time zone issue, create a density plot of the fractional hour when tornadoes occur.

a. Use the `separate()` function to create three new columns (*hour*, *min*, *sec*) from the `time` column.
b. Add another column, named `time2`, that gives the fractional number of hours that a tornado occurred.
c. Generate a density plot of `time2`.

4.3 Problem 3: Pew Survey

Your Turn #8 : Pew Survey

Results from a pew survey were presented in a non-tidy (table) format where the column headers are *values* instead of *variable names*. That is, the data are in *wide* formate, and we desire the *long* format. The data can be found https://github.com/hadley/tidyr/blob/master/vignettes/pew.csv.

a. Load the data into R. The url to the raw data is https://raw.githubusercontent.com/hadley/tidyr/master/vignettes/pew.csv
b. What are the three variables in the data?
c. Use `gather()` to make the data *tidy* (i.e., long format, with one column for each variable).
d. Make a graphic from the long data comparing the distribution of income between `Catholic` and `Evangelical Prot`.

5 Other functions in `tidyr` package

function	description
`replace_na()`	Replace NA's with specific values
`fill()`	Fills missing values in using the previous entry. This is useful in the common output format where values are not repeated, they're recorded each time they change.

function	description
`extract()`	check out `separate()`, but allows different patterns
`expand()`	convert *implicit* missing values (i.e., missing rows) to *explicit* missing values (include rows with `NA`s)
`complete()`	good for tables (filling in missing with 0 counts)