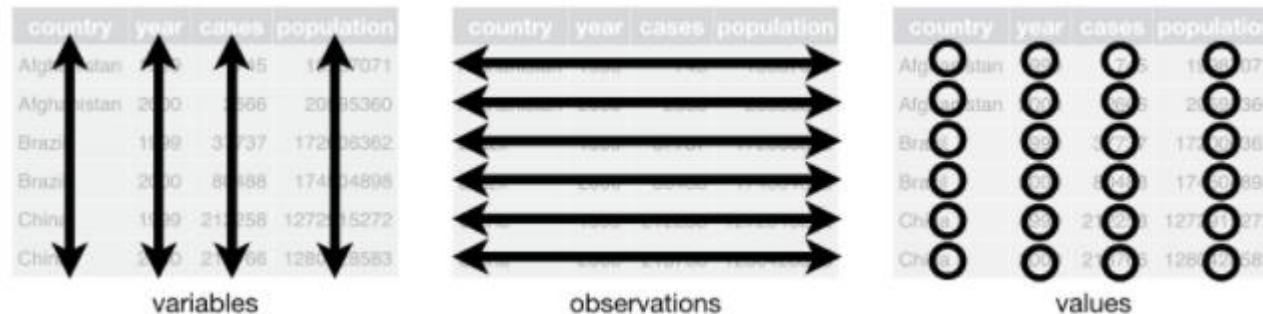


Data Wrangling - tidyr

“Tidy datasets are all alike, but every messy dataset is messy in its own way.” — Hadley Wickham

Tidy data:

- **Every column is variable**
- **Every row is an observation.**
- **Every cell is a single value.**



Why tidyr?

- **If you have a consistent data structure, it's easier to learn the tools that work with it.**
- **Most built-in R functions work with vectors of values. That makes transforming tidy data feel particularly natural.**
- **dplyr, ggplot2, and all the other packages in the tidyverse are designed to work with tidy data.**

Example Data

Representation of the same data in multiple ways

table1

```
#> # A tibble: 6 x 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
```

table2

```
#> # A tibble: 12 x 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
#> # ... with 6 more rows
```

table3

```
#> # A tibble: 6 x 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
```

table4a # cases

```
#> # A tibble: 3 x 3
#>   country `1999` `2000`
#>   * <chr>      <int> <int>
#> 1 Afghanistan     745     2666
#> 2 Brazil          37737    80488
#> 3 China          212258    213766
```

table4b # population

```
#> # A tibble: 3 x 3
#>   country `1999` `2000`
#>   * <chr>      <int> <int>
#> 1 Afghanistan 19987071 20595360
#> 2 Brazil      172006362 174504898
#> 3 China      1272915272 1280428583
```

Pivoting

- **One variable might be spread across multiple columns. (Use `Pivot_longer()`)**

```
table4a # cases
#> # A tibble: 3 x 3
#>   country `1999` `2000`
#> * <chr>   <int> <int>
#> 1 Afghanistan  745  2666
#> 2 Brazil      37737 80488
#> 3 China       212258 213766
```

```
table4b # population
#> # A tibble: 3 x 3
#>   country `1999` `2000`
#> * <chr>   <int> <int>
#> 1 Afghanistan 19987071 20595360
#> 2 Brazil      172006362 174504898
#> 3 China       1272915272 1280428583
```

- **One observation might be scattered across multiple rows. (Use `Pivot_wider()`)**

Apply Pivot_longer() to table4a

```
table4a %>%  
  pivot_longer(c(`1999`, `2000`), names_to = "year", values_to = "cases")  
#> # A tibble: 6 x 3  
#>   country   year  cases  
#>   <chr>    <chr> <int>  
#> 1 Afghanistan 1999    745  
#> 2 Afghanistan 2000   2666  
#> 3 Brazil      1999  37737  
#> 4 Brazil      2000  80488  
#> 5 China       1999 212258  
#> 6 China       2000 213766
```

country	year	cases
Afghanistan	1999	745
Afghanistan	2000	2666
Brazil	1999	37737
Brazil	2000	80488
China	1999	212258
China	2000	213766

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

table4

Apply Pivot_longer() and combine data

```
tidy4a <- table4a %>%  
  pivot_longer(c(`1999`, `2000`), names_to = "year", values_to = "cases")  
tidy4b <- table4b %>%  
  pivot_longer(c(`1999`, `2000`), names_to = "year", values_to = "population")  
left_join(tidy4a, tidy4b)  
#> Joining, by = c("country", "year")  
#> # A tibble: 6 x 4  
#>   country   year cases population  
#>   <chr>    <chr> <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
```

```
table4a # cases  
#> # A tibble: 3 x 3  
#>   country `1999` `2000`  
#> * <chr>   <int> <int>  
#> 1 Afghanistan    745  2666  
#> 2 Brazil      37737 80488  
#> 3 China      212258 213766
```

```
table4b # population  
#> # A tibble: 3 x 3  
#>   country `1999` `2000`  
#> * <chr>   <int> <int>  
#> 1 Afghanistan 19987071 20595360  
#> 2 Brazil      172006362 174504898  
#> 3 China      1272915272 1280428583
```

Pivoting

- One variable might be spread across multiple columns. (Use `Pivot_longer()`)
- One observation might be scattered across multiple rows. (Use `Pivot_wider()`)

```
table2
#> # A tibble: 12 x 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
#> # ... with 6 more rows
```

Apply Pivot_wider()

```
table2 %>%  
  pivot_wider(names_from = type, values_from = count)  
#> # A tibble: 6 x 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
```

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

table2

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

Separating and uniting

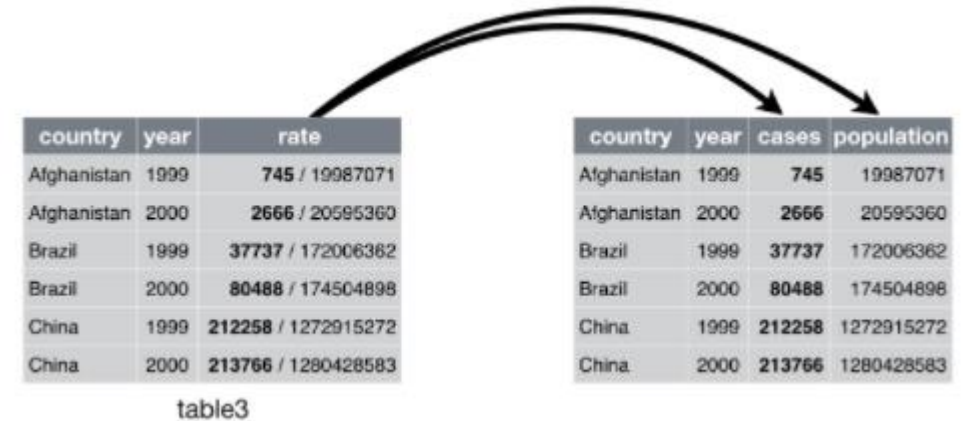
- **One column contains two variables (Use separate())**

```
table3
#> # A tibble: 6 x 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
```

- **Single variable is spread across multiple columns.
(Use unite())**

Apply separate()

```
table3 %>%  
  separate(rate, into = c("cases", "population"))  
#> # A tibble: 6 x 4  
#>   country    year cases population  
#>   <chr>    <int> <chr>   <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
```




Separating and uniting

- One column contains two variables (Use `separate()`)
- **Single variable is spread across multiple columns.**
(Use `unite()`)

	country	century	year	rate
	<chr>	<chr>	<chr>	<chr>
1	Afghanistan	19	99	745/19987071
2	Afghanistan	20	00	2666/20595360
3	Brazil	19	99	37737/172006362
4	Brazil	20	00	80488/174504898
5	China	19	99	212258/1272915272
6	China	20	00	213766/1280428583

Apply unite()

```
table5 %>%  
  unite(new, century, year, sep = "")  
#> # A tibble: 6 x 3  
#>   country    new    rate  
#>   <chr>    <chr> <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
```



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

country	century	year	rate
Afghanistan	19	99	745 / 19987071
Afghanistan	20	00	2666 / 20595360
Brazil	19	99	37737 / 172006362
Brazil	20	00	80488 / 174504898
China	19	99	212258 / 1272915272
China	20	00	213766 / 1280428583

table6

Functional Programming

- **For loops are quite verbose, and require quite a bit of bookkeeping code that is duplicated for every for loop.**
- **Functional programming offers tools to extract out this duplicated code, so each common for loop pattern gets its own function.**

For loops

Random data

```
df <- tibble(  
  a = rnorm(10),  
  b = rnorm(10),  
  c = rnorm(10),  
  d = rnorm(10)  
)
```

With for loops

```
output <- vector("double", ncol(df)) # 1. output  
for (i in seq_along(df)) {          # 2. sequence  
  output[[i]] <- median(df[[i]])    # 3. body  
}  
output  
#> [1] -0.24576245 -0.28730721 -0.05669771 0.14426335
```

To calculate median

```
median(df$a)  
#> [1] -0.2457625  
median(df$b)  
#> [1] -0.2873072  
median(df$c)  
#> [1] -0.05669771  
median(df$d)  
#> [1] 0.1442633
```

Three components

The **output**: `output <- vector("double", length(x)).`

Allocate sufficient space for the output.

(If you grow the for loop at each iteration using `c()` (for example), your for loop will be very slow)

The **sequence**: `i in seq_along(df).`

what to loop over:

each run of the for loop will assign `i` to a different value from `seq_along(df)`

The **body**: `output[[i]] <- median(df[[i]]).`

This is the code that does the work.

```
output <- vector("double", ncol(df)) # 1. output
for (i in seq_along(df)) {          # 2. sequence
  output[[i]] <- median(df[[i]])    # 3. body
}
output
#> [1] -0.24576245 -0.28730721 -0.05669771  0.14426335
```

For loops vs. functionals

Possible to wrap up for loops in a function

```
col_mean <- function(df) {  
  output <- vector("double", ncol(df))  
  for (i in seq_along(df)) {  
    output[[i]] <- mean(df[[i]])  
  }  
  output  
}
```

```
col_median <- function(df) {  
  output <- vector("double", ncol(df))  
  for (i in seq_along(df)) {  
    output[[i]] <- median(df[[i]])  
  }  
  output  
}
```

```
col_sd <- function(df) {  
  output <- vector("double", ncol(df))  
  for (i in seq_along(df)) {  
    output[[i]] <- sd(df[[i]])  
  }  
  output  
}
```

```
col_summary <- function(df, fun) {  
  out <- vector("double", length(df))  
  for (i in seq_along(df)) {  
    out[i] <- fun(df[[i]])  
  }  
  out  
}  
col_summary(df, median)  
#> [1] -0.51850298 0.02779864 0.17295591 -0.61163819  
col_summary(df, mean)  
#> [1] -0.3260369 0.1356639 0.4291403 -0.2498034
```


The map function (purrr)

the purrr package provides a family of functions for looping patterns over a vector

- **map()** makes a list
- **map_lgl()** makes a logical vector
- **map_int()** makes an integer vector
- **map_dbl()** makes a double vector
- **map_chr()** makes a character vector

Alternatives: apply, lapply, etc

The map function (purrr)

```
df %>% map_dbl(mean)
#>      a      b      c      d
#> -0.3260369 0.1356639 0.4291403 -0.2498034
df %>% map_dbl(median)
#>      a      b      c      d
#> -0.51850298 0.02779864 0.17295591 -0.61163819
df %>% map_dbl(sd)
#>      a      b      c      d
#> 0.9214834 0.4848945 0.9816016 1.1563324
```

You can define a function in a map function

```
models <- mtcars %>%
  split(.$cyl) %>%
  map(function(df) lm(mpg ~ wt, data = df))
```

```
models <- mtcars %>%
  split(.$cyl) %>%
  map(~lm(mpg ~ wt, data = .))
```

To extract a component

```
models %>%  
  map(summary) %>%  
  map_dbl(~.$r.squared)  
#>      4      6      8  
#> 0.5086326 0.4645102 0.4229655
```

```
models %>%  
  map(summary) %>%  
  map_dbl("r.squared")  
#>      4      6      8  
#> 0.5086326 0.4645102 0.4229655
```

You can also use an integer to select elements by position

```
x <- list(list(1, 2, 3), list(4, 5, 6), list(7, 8, 9))  
x %>% map_dbl(2)  
#> [1] 2 5 8
```