STATS 220

Tidy data🧹

What you think about data science 🤩

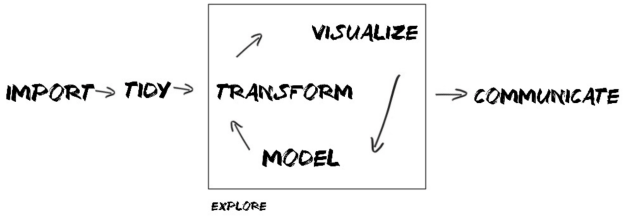


image credit: Hilary Parker

What data science is in reality 😭

image credit: Hilary Parker

tidy data ≠ clean data

The `movies` data is tidy but not clean.

```
#> # A tibble: 5 x 16
#>   Release_Date US_DVD_Sales Title      US_Gross Worldwide_Gross Production_Budg…
#>   <chr>               <int> <chr>         <int>           <dbl>            <int>
#> 1 9-Mar-94               NA Four Wedd… 52700832       242895809          4500000
#> 2 18-Oct-06              NA 51 Birch …    84689           84689           350000
#> 3 1963-01-01             NA 55 Days a… 10000000        10000000         17000000
#> 4 <NA>                   NA Drei           0               0            7200000
#> 5 16-Jan-98              NA The Dress   16556           16556            2650000
#> # … with 10 more variables: MPAA_Rating <chr>, Running_Time_min <int>,
#> #   Distributor <chr>, Source <chr>, Major_Genre <chr>, Creative_Type <chr>,
#> #   Director <chr>, Rotten_Tomatoes_Rating <int>, IMDB_Rating <dbl>,
#> #   IMDB_Votes <int>
```


tidy data ≠ clean data

They are tidy and clean in their own way.

`> time_use`

```
#> # A tibble: 28 x 3
#>   country    category            minutes
#>   <chr>      <chr>                 <dbl>
#> 1 New Zeala… Paid work               241
#> 2 USA        Paid work               251.
#> 3 New Zeala… Education                29
#> 4 USA        Education                31.4
#> 5 New Zeala… Care for household…      30
#> 6 USA        Care for household…      30.6
#> # … with 22 more rows
```

`> countrycode`

```
#> # A tibble: 2 x 2
#>   country country_name
#>   <chr>   <chr>
#> 1 NZL     New Zealand
#> 2 USA     United States
```


Tidy data describes a standard way of storing data in a consistent format.

Your turn

01:00

Tuberculosis data from WHO (`data/tb.csv`):

1. Is `tb` tidy data?
2. What are the data observations? What are the data variables?

```
tb
```

```
#> # A tibble: 5,769 x 22
#>   iso2   year  m_04 m_514 m_014 m_1524 m_2534 m_3544 m_4554 m_5564  m_65   m_u
#>   <chr> <dbl> <dbl> <dbl> <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl> <dbl> <dbl>
#> 1 AD     1989    NA    NA    NA     NA     NA     NA     NA     NA    NA    NA
#> 2 AD     1990    NA    NA    NA     NA     NA     NA     NA     NA    NA    NA
#> 3 AD     1991    NA    NA    NA     NA     NA     NA     NA     NA    NA    NA
#> 4 AD     1992    NA    NA    NA     NA     NA     NA     NA     NA    NA    NA
#> 5 AD     1993    NA    NA    NA     NA     NA     NA     NA     NA    NA    NA
#> 6 AD     1994    NA    NA    NA     NA     NA     NA     NA     NA    NA    NA
#> # … with 5,763 more rows, and 10 more variables: f_04 <dbl>, f_514 <dbl>,
#> #   f_014 <dbl>, f_1524 <dbl>, f_2534 <dbl>, f_3544 <dbl>, f_4554 <dbl>,
#> #   f_5564 <dbl>, f_65 <dbl>, f_u <dbl>
```

one data, many representations

wide

id	x	y	z
1	a	c	e
2	b	d	f

long

id	key	val
1	x	a
2	x	b
1	y	c
2	y	d
1	z	e
2	z	f

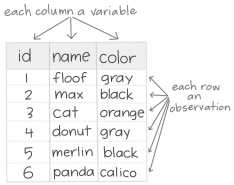
image credit: Garrick Aden-Buie

"TIDY DATA is a standard way of mapping the meaning of a dataset to its structure."

–HADLEY WICKHAM

In tidy data:

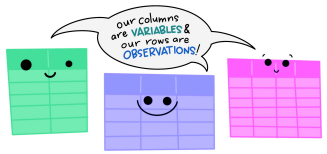
- each variable forms a column
- each observation forms a row
- each cell is a single measurement



id	name	color
1	floof	gray
2	max	black
3	cat	orange
4	donut	gray
5	merlin	black
6	panda	calico

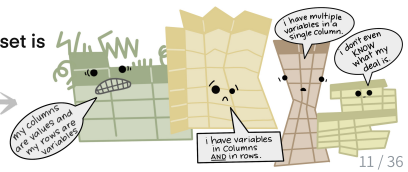
Wickham, H. (2014). Tidy Data. Journal of Statistical Software 59 (10). DOI: 10.18637/jss.v059.i10

The standard structure of tidy data means that "tidy datasets are all alike..."



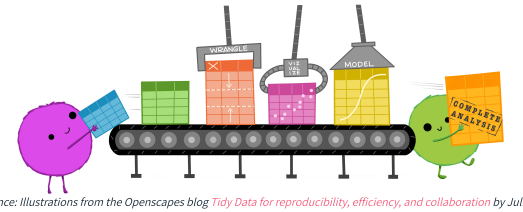
"...but every messy dataset is messy in its own way."

–HADLEY WICKHAM



Making friends with tidy data

- one set of consistent tools for different datasets
- easier for automation and iteration



reference: Illustrations from the Openscapes blog Tidy Data for reproducibility, efficiency, and collaboration by Julia Lowndes and Allison Horst

Get data into tidy format

type	function()	function()
pivoting	pivot_longer()	pivot_wider()
splitting/combining	seperate()	unite()
nesting/unnesting	nest()	unnest()
missing	complete()	fill()

✖ Messy

```
#> # A tibble: 5,769 x 22
#>   iso2   year  m_04 m_514 m_014
#>   <chr> <dbl> <dbl> <dbl> <dbl>
#> 1 AD     1989    NA    NA    NA
#> 2 AD     1990    NA    NA    NA
#> 3 AD     1991    NA    NA    NA
#> 4 AD     1992    NA    NA    NA
#> 5 AD     1993    NA    NA    NA
#> 6 AD     1994    NA    NA    NA
#> # … with 5,763 more rows, and 17
#> #   more variables: m_1524 <dbl>,
#> #   m_2534 <dbl>, m_3544 <dbl>,
#> #   m_4554 <dbl>, m_5564 <dbl>,
#> #   m_65 <dbl>, m_u <dbl>,
#> #   f_04 <dbl>, f_514 <dbl>,
#> #   f_014 <dbl>, f_1524 <dbl>,
#> #   f_2534 <dbl>, f_3544 <dbl>,
#> #   f_4554 <dbl>, f_5564 <dbl>,
#> #   f_65 <dbl>, f_u <dbl>
```

✔ Tidy

```
#> # A tibble: 115,380 x 5
#>   iso2   year sex   age   cases
#>   <chr> <dbl> <chr> <chr> <dbl>
#> 1 AD     1989 m     04        0
#> 2 AD     1989 m     514       0
#> 3 AD     1989 m     014       0
#> 4 AD     1989 m     1524      0
#> 5 AD     1989 m     2534      0
#> 6 AD     1989 m     3544      0
#> # … with 115,374 more rows
```


- pivot

› `pivot_longer()` a wider-format data

```
library(tidyverse) # library(tidyr)
tb %>%
  pivot_longer(
    cols = m_04:f_u, # cols in the data for pivoting
    names_to = "sex_age", # new col contains old headers
    values_to = "cases") # new col contains old values
```

```
#> # A tibble: 115,380 x 4
#>   iso2   year sex_age cases
#>   <chr> <dbl> <chr>   <dbl>
#> 1 AD     1989 m_04       NA
#> 2 AD     1989 m_514      NA
#> 3 AD     1989 m_014      NA
#> 4 AD     1989 m_1524     NA
#> 5 AD     1989 m_2534     NA
#> 6 AD     1989 m_3544     NA
#> # … with 115,374 more rows
```


- pivot

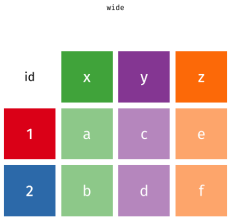


image credit: Garrick Aden-Buie & Mara Averick

- pivot
- **split**

› `seperate()` a character column into multiple columns

```
tb %>%
  pivot_longer(cols = m_04:f_u,
    names_to = "sex_age", values_to = "cases") %>%
  separate(sex_age, into = c("sex", "age"), sep = "_")
```

```
#> # A tibble: 115,380 x 5
#>   iso2   year sex   age   cases
#>   <chr> <dbl> <chr> <chr> <dbl>
#> 1 AD     1989 m     04       NA
#> 2 AD     1989 m     514      NA
#> 3 AD     1989 m     014      NA
#> 4 AD     1989 m     1524     NA
#> 5 AD     1989 m     2534     NA
#> 6 AD     1989 m     3544     NA
#> # … with 115,374 more rows
```


- pivot
- split
- **fill**

› `fill()` in `NA` with previous (`"down"`) or next (`"up"`) value

```
tb_tidy <- tb %>%
  pivot_longer(cols = m_04:f_u,
    names_to = "sex_age", values_to = "cases") %>%
  separate(sex_age, into = c("sex", "age"), sep = "_") %>%
  group_by(iso2) %>%
  fill(cases, .direction = "updown") %>%
  ungroup()
```

```
#> # A tibble: 115,380 x 5
#>   iso2   year sex   age   cases
#>   <chr> <dbl> <chr> <chr> <dbl>
#> 1 AD     1989 m     04        0
#> 2 AD     1989 m     514       0
#> 3 AD     1989 m     014       0
#> 4 AD     1989 m     1524      0
#> 5 AD     1989 m     2534      0
#> 6 AD     1989 m     3544      0
#> # … with 115,374 more rows
```


- pivot
- split
- fill
- **nest**

› `nest()` multiple columns into a list-column

```
tb_tidy %>%
  nest(data = -iso2)
```

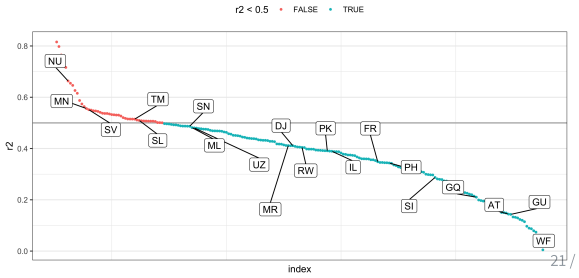
```
#> # A tibble: 213 x 2
#>   iso2  data
#>   <chr> <list>
#> 1 AD    <tibble[,4] [380 × 4]>
#> 2 AE    <tibble[,4] [520 × 4]>
#> 3 AF    <tibble[,4] [480 × 4]>
#> 4 AG    <tibble[,4] [540 × 4]>
#> 5 AI    <tibble[,4] [440 × 4]>
#> 6 AL    <tibble[,4] [540 × 4]>
#> # … with 207 more rows
```

Building many models*

```
tb_fit <- tb_tidy %>%
  nest(data = -iso2) %>%
  mutate( # map() for week 11
    model = map(data, ~ lm(cases ~ year + sex + age, data = .)),
    r2 = map_dbl(model, ~ broom::glance(.)$r.squared)
  )
```

```
#> # A tibble: 213 x 4
#>   iso2  data                  model     r2
#>   <chr> <list>                <list> <dbl>
#> 1 AD    <tibble[,4] [380 × 4]> <lm>   0.165
#> 2 AE    <tibble[,4] [520 × 4]> <lm>   0.133
#> 3 AF    <tibble[,4] [480 × 4]> <lm>   0.487
#> 4 AG    <tibble[,4] [540 × 4]> <lm>   0.220
#> 5 AI    <tibble[,4] [440 × 4]> <lm>   0.515
#> 6 AL    <tibble[,4] [540 × 4]> <lm>   0.478
#> # … with 207 more rows
```

› Plot › Code



Your turn

01:00

Auckland weather data from GHCND (`data/ghcnd/ghcnd-akl.csv`):

1. Is `aklweather` tidy data?
2. What are the data observations? What are the data variables?

```
aklweather
```

```
#> # A tibble: 2,974 x 3
#>   date       datatype value
#>   <date>     <chr>    <dbl>
#> 1 2019-01-01 PRCP         0
#> 2 2019-01-01 TAVG       206
#> 3 2019-01-01 TMAX       232
#> 4 2019-01-01 TMIN       188
#> 5 2019-01-02 PRCP         5
#> 6 2019-01-02 TAVG       207
#> # … with 2,968 more rows
```


✗ Messy

```
#> # A tibble: 2,974 x 3
#>   date       datatype value
#>   <date>     <chr>    <dbl>
#> 1 2019-01-01 PRCP         0
#> 2 2019-01-01 TAVG       206
#> 3 2019-01-01 TMAX       232
#> 4 2019-01-01 TMIN       188
#> 5 2019-01-02 PRCP         5
#> 6 2019-01-02 TAVG       207
#> # … with 2,968 more rows
```

```
aklweather <- read_csv2(
  "data/ghcnd/ghcnd-akl.csv",
  col_types = cols_only(
    date = "D", datatype = "c",
    value = "d"))
aklweather
```

✓ Tidy

```
#> # A tibble: 816 x 5
#>   date        PRCP  TAVG  TMAX  TMIN
#>   <date>     <dbl> <dbl> <dbl> <dbl>
#> 1 2019-01-01     0   206   232   188
#> 2 2019-01-02     5   207   230   183
#> 3 2019-01-03     0   211   241   184
#> 4 2019-01-04     0   192   229    NA
#> 5 2019-01-05     0   200   233   150
#> 6 2019-01-06     0   213   237   169
#> # … with 810 more rows
```


- calibrate

› calibrate the measurements

```
aklweather %>%
  mutate(value = value / 10)
```

```
#> # A tibble: 2,974 x 3
#>   date       datatype value
#>   <date>     <chr>    <dbl>
#> 1 2019-01-01 PRCP       0
#> 2 2019-01-01 TAVG      20.6
#> 3 2019-01-01 TMAX      23.2
#> 4 2019-01-01 TMIN      18.8
#> 5 2019-01-02 PRCP       0.5
#> 6 2019-01-02 TAVG      20.7
#> # … with 2,968 more rows
```

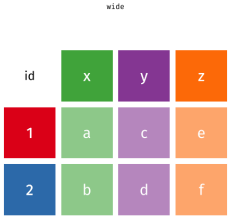
- calibrate
- **pivot**

› `pivot_wider()` a longer-format data

```
aklweather %>%
  mutate(value = value / 10) %>%
  pivot_wider(
    names_from = datatype, # new headers from old `datatype` val
    values_from = value)  # new col contains old `value`
```

```
#> # A tibble: 816 x 5
#>   date        PRCP  TAVG  TMAX  TMIN
#>   <date>     <dbl> <dbl> <dbl> <dbl>
#> 1 2019-01-01   0    20.6  23.2  18.8
#> 2 2019-01-02   0.5  20.7  23    18.3
#> 3 2019-01-03   0    21.1  24.1  18.4
#> 4 2019-01-04   0    19.2  22.9  NA
#> 5 2019-01-05   0    20    23.3  15
#> 6 2019-01-06   0    21.3  23.7  16.9
#> # … with 810 more rows
```


- calibrate
- **pivot**



- calibrate
- pivot
- **rename**

› `rename_with()` renames columns using a function

```
aklweather_tidy <- aklweather %>%
  mutate(value = value / 10) %>%
  pivot_wider(
    names_from = datatype,
    values_from = value) %>%
  rename_with(tolower)
aklweather_tidy
```

```
#> # A tibble: 816 x 5
#>   date        prcp  tavg  tmax  tmin
#>   <date>     <dbl> <dbl> <dbl> <dbl>
#> 1 2019-01-01   0    20.6  23.2  18.8
#> 2 2019-01-02   0.5  20.7  23    18.3
#> 3 2019-01-03   0    21.1  24.1  18.4
#> 4 2019-01-04   0    19.2  22.9  NA
#> 5 2019-01-05   0    20    23.3  15
#> 6 2019-01-06   0    21.3  23.7  16.9
#> # … with 810 more rows
```


- calibrate
- pivot
- rename
- **complete**

› `complete()` data with missing combinations of data

```
library(lubridate)
aklweather_tidy %>%
  complete(date = full_seq(
    ymd(c("2019-01-01", "2021-04-01")), 1))
```

```
#> # A tibble: 822 x 5
#>   date        prcp  tavg  tmax  tmin
#>   <date>     <dbl> <dbl> <dbl> <dbl>
#> 1 2019-01-01   0    20.6  23.2  18.8
#> 2 2019-01-02   0.5  20.7  23    18.3
#> 3 2019-01-03   0    21.1  24.1  18.4
#> 4 2019-01-04   0    19.2  22.9  NA
#> 5 2019-01-05   0    20    23.3  15
#> 6 2019-01-06   0    21.3  23.7  16.9
#> # … with 816 more rows
```

- calibrate
- pivot
- rename
- **complete**

› implicit missing records

```
akl_weather_tidy %>%
  complete(date = full_seq(
    ymd(c("2019-01-01", "2021-04-01")), 1)) %>%
  anti_join(akl_weather_tidy)
```

```
#> # A tibble: 6 x 5
#>   date        prcp  tavg  tmax  tmin
#>   <date>     <dbl> <dbl> <dbl> <dbl>
#> 1 2019-02-16    NA    NA    NA    NA
#> 2 2019-02-17    NA    NA    NA    NA
#> 3 2019-02-18    NA    NA    NA    NA
#> 4 2021-02-11    NA    NA    NA    NA
#> 5 2021-02-12    NA    NA    NA    NA
#> 6 2021-02-20    NA    NA    NA    NA
```


- calibrate
- pivot
- rename
- complete
- **wrangle**

```
akl_prcp <- akl_weather_tidy %>%
  complete(
    date = full_seq(ymd(c("2019-01-01", "2021-04-01")), 1),
    fill = list(prcp = 0)
  ) %>%
  group_by(yearmonth = floor_date(date, "1 month")) %>%
  mutate(cum_prcp = cumsum(prcp)) %>%
  ungroup()
akl_prcp
```

```
#> # A tibble: 822 x 7
#>   date        prcp  tavg  tmax  tmin yearmonth  cum_prcp
#>   <date>     <dbl> <dbl> <dbl> <dbl> <date>        <dbl>
#> 1 2019-01-01   0    20.6  23.2  18.8 2019-01-01      0
#> 2 2019-01-02   0.5  20.7  23    18.3 2019-01-01      0.5
#> 3 2019-01-03   0    21.1  24.1  18.4 2019-01-01      0.5
#> 4 2019-01-04   0    19.2  22.9  NA   2019-01-01      0.5
#> 5 2019-01-05   0    20    23.3  15   2019-01-01      0.5
#> 6 2019-01-06   0    21.3  23.7  16.9 2019-01-01      0.5
#> # … with 816 more rows
```


Your turn

> *1. Why do I fill `0` to missing `prcp`, instead of leaving `NA` as is?*
> *2. Why do I calculate monthly cumulative precipitations?*

00:30

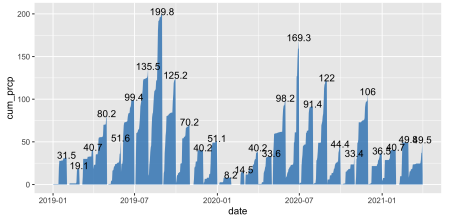
```
akl_weather_tidy %>%
  complete(date = full_seq(
    ymd(c("2019-01-01", "2021-04-01")),
    1)) %>%
  filter(is.na(prcp))
```

```
#> # A tibble: 13 x 5
#>    date        prcp  tavg  tmax  tmin
#>    <date>     <dbl> <dbl> <dbl> <dbl>
#>  1 2019-02-16    NA  NA    NA    NA
#>  2 2019-02-17    NA  NA    NA    NA
#>  3 2019-02-18    NA  NA    NA    NA
#>  4 2019-07-01    NA  13.4  18.2  NA
#>  5 2019-07-02    NA  15.4  17    11.6
#>  6 2019-07-03    NA  16.8  18.2  13.6
#>  7 2019-11-01    NA  14.4  17    12.8
#>  8 2019-11-29    NA  19.7  25.1  NA
#>  9 2020-04-07    NA  16.9  22.3  NA
#> 10 2020-10-20    NA  17    NA    NA
#> 11 2021-02-11    NA  NA    NA    NA
#> 12 2021-02-12    NA  NA    NA    NA
#> 13 2021-02-20    NA  NA    NA    NA
```


- calibrate
- pivot
- rename
- complete
- wrangle
- **visualise**

Area plot for monthly cumulative rainfall

› Plot › Code



- calibrate
- pivot
- rename
- complete
- **wrangle**

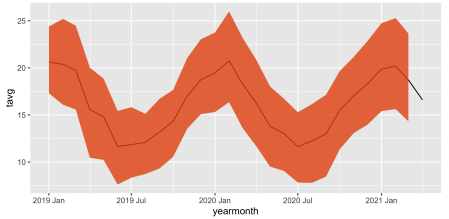
```
akl_monthly_temp <- aklweather_tidy %>%
  group_by(yearmonth = floor_date(date, "1 month")) %>%
  summarise(
    tavg = mean(tavg, na.rm = TRUE),
    tmax = mean(tmax, na.rm = TRUE),
    tmin = mean(tmin, na.rm = TRUE)
  )
akl_monthly_temp
```

```
#> # A tibble: 28 x 4
#>   yearmonth    tavg  tmax  tmin
#>   <date>      <dbl> <dbl> <dbl>
#> 1 2019-01-01  20.6  24.4 17.3
#> 2 2019-02-01  20.4  25.2 16.1
#> 3 2019-03-01  19.7  24.5 15.6
#> 4 2019-04-01  15.6  20.0 10.5
#> 5 2019-05-01  14.8  18.9 10.2
#> 6 2019-06-01  11.7  15.4  7.62
#> # … with 22 more rows
```


- calibrate
- pivot
- rename
- complete
- wrangle
- **visualise**

Ribbon plot for monthly temperatures

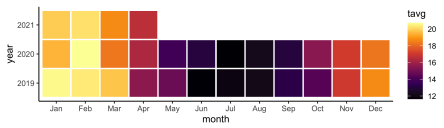
› Plot › Code



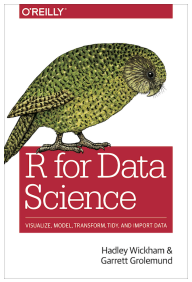
- calibrate
- pivot
- rename
- complete
- wrangle
- **visualise**

Heatmap for monthly average temperatures

› Plot › Code



Reading



› Tidy data
› {tidyr} cheatsheet