

Tidy Data

Brad Stieber

2018-10-01

Introduction

Idea (the theory)

Execution (the practice)

Conclusion

Find the repository for this presentation [on my GitHub](#)

Introduction

Goals for this talk

My goal is for you to walk away from this presentation with an understanding of:

- Tidy data philosophy

Goals for this talk

My goal is for you to walk away from this presentation with an understanding of:

- Tidy data philosophy
- **tidyverse** data terminology

Goals for this talk

My goal is for you to walk away from this presentation with an understanding of:

- Tidy data philosophy
- **tidyverse** data terminology
- Common types of *untidy* data

Goals for this talk

My goal is for you to walk away from this presentation with an understanding of:

- Tidy data philosophy
- **tidyverse** data terminology
- Common types of *untidy* data
- Operations for tidying up

Goals for this talk

My goal is for you to walk away from this presentation with an understanding of:

- Tidy data philosophy
- **tidyverse** data terminology
- Common types of *untidy* data
- Operations for tidying up
- Displaying tidy data

What this is based off of

Most of what follows is based off of [Hadley Wickham's paper](#) on tidy data. I would strongly recommend reading that paper.

If you're looking for a practical introduction, [Hadley Wickham has one of those too](#).



I also borrow a bit from other resources (which will be listed at the end), as well as my own experience working with tidy *and* untidy datasets.

But mostly...



Idea (the theory)

Why tidy data?

- Consistency

Why tidy data?

- Consistency
- Rely on vectorization (in R and pandas), and expected/desired behavior in grouped aggregation (excel, tableau)

Why tidy data?

- Consistency
- Rely on vectorization (in R and pandas), and expected/desired behavior in grouped aggregation (excel, tableau)
- Foresight

What is tidy data

There are three qualities a dataset must have to be considered “tidy”

1. Each variable forms a column.

What is tidy data

There are three qualities a dataset must have to be considered “tidy”

1. Each variable forms a column.
2. Each observation forms a row.

What is tidy data

There are three qualities a dataset must have to be considered “tidy”

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

The Language of Tidy Data

- Dataset: a collection of values (e.g. [iris data](#))
- Variable: all values that measure the same underlying attribute (e.g. height, width)
- Values: a specific measurement or attribute for a variable (e.g. \$100)
- Observation: all values measured on the same unit (like a person, or a day, or a race) across variables

It's usually easy to figure out things like *observations* and *variables* for a given dataset, but defining them in the abstract can be difficult.

The Data Tidying Operations

Getting data into a tidy format first requires understanding the three qualities of tidy data, as well as the five most common types of untidy data.

Then, we can get most forms of untidy data to be tidy by utilizing four verbs of data tidying

- **gather**: takes multiple columns, and gathers them into key-value pairs. it makes “wide” data longer

The Data Tidying Operations

Getting data into a tidy format first requires understanding the three qualities of tidy data, as well as the five most common types of untidy data.

Then, we can get most forms of untidy data to be tidy by utilizing four verbs of data tidying

- **gather**: takes multiple columns, and gathers them into key-value pairs. it makes “wide” data longer
- **spread**: takes two columns (key & value) and spreads in to multiple columns. it makes “long” data wider

The Data Tidying Operations

Getting data into a tidy format first requires understanding the three qualities of tidy data, as well as the five most common types of untidy data.

Then, we can get most forms of untidy data to be tidy by utilizing four verbs of data tidying

- **gather**: takes multiple columns, and gathers them into key-value pairs. it makes “wide” data longer
- **spread**: takes two columns (key & value) and spreads in to multiple columns. it makes “long” data wider
- **separate**: turns a single character column into multiple columns, based on a regular expression or specific positions

The Data Tidying Operations

Getting data into a tidy format first requires understanding the three qualities of tidy data, as well as the five most common types of untidy data.

Then, we can get most forms of untidy data to be tidy by utilizing four verbs of data tidying

- **gather**: takes multiple columns, and gathers them into key-value pairs. it makes “wide” data longer
- **spread**: takes two columns (key & value) and spreads in to multiple columns. it makes “long” data wider
- **separate**: turns a single character column into multiple columns, based on a regular expression or specific positions
- **unite**: concatenate multiple columns into one

Execution (the practice)

Five common types of untidy data

Here are the five most common types of untidy data you're likely to experience "in the wild":

- Column headers are values, not variable names.
- Multiple variables are stored in one column.
- Variables are stored in both rows and columns.
- Multiple types of observational units are stored in the same table.
- A single observational unit is stored in multiple tables.

We'll go through examples of each of the five.

BRACE YOURSELVES,



UNTIDY DATA IS COMING

1. Column headers are values, not variable names

The first dataset we'll look at comes from the WHO and displays the number of TB cases for three countries in two years.

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

This data is too *wide*, as 1999 and 2000 are **values** for a **variable** we could call *year*.

Although difficult to analyze, this form of data storage is helpful for presentation and data entry.

How would we tidy up?

Tidying # 1

Need to `gather` columns into key-value (year-cases) pairs:

```
tb_data %>%  
  gather(key = year,  
         value = tb_cases,  
         -country)  
  
## # A tibble: 6 x 3  
##   country      year tb_cases  
##   <chr>      <chr>   <int>  
## 1 Afghanistan 1999       745  
## 2 Brazil      1999     37737  
## 3 China       1999    212258  
## # ... with 3 more rows
```

2. Multiple variables are stored in one column

The next table has two columns, but it should have four. How would you work with this data without tidying it first?

Hair - Eye - Sex	n
Black - Brown - Male	32
Brown - Brown - Male	53
Red - Brown - Male	10
Blond - Brown - Male	3
Black - Blue - Male	11
Brown - Blue - Male	50

The HairEyeColor **variable** actually has **values** for three separate **variables** stored within it.

How would we tidy up?

Tidying #2 (1/2)

We need to `separate` one column (Hair - Eye - Sex) into multiple columns (hair, eye, sex)

```
hec_untidy %>%  
  separate(col = `Hair - Eye - Sex`,  
           into = c('hair', 'eye', 'sex'))
```

```
## # A tibble: 6 x 4  
##   hair  eye  sex      n  
##   <chr> <chr> <chr> <dbl>  
## 1 Black Brown Male    32  
## 2 Brown Brown Male    53  
## 3 Red   Brown Male    10  
## # ... with 3 more rows
```

Tidying #2 (2/2)

Could go a step further and use `uncount` (the opposite of `dplyr::count`):

```
hec_untidy %>%  
  separate(col = `Hair - Eye - Sex`,  
            into = c('hair', 'eye', 'sex')) %>%  
  uncount(n)
```

```
## # A tibble: 159 x 3  
##   hair  eye  sex  
##   <chr> <chr> <chr>  
## 1 Black Brown Male  
## 2 Black Brown Male  
## 3 Black Brown Male  
## # ... with 156 more rows
```

3. Variables are stored in both rows and columns

This is the most complicated form of untidy data, and typically requires a bit more massaging.

year	month	stock	d1	d2	d3	d4
2000	1	CAC	1772.80	1750.50	1718.00	1708.10
2000	1	DAX	1628.75	1613.63	1606.51	1621.04
2000	1	FTSE	2443.60	2460.20	2448.20	2470.40
2000	1	SMI	1678.10	1688.50	1678.60	1684.10

How would we tidy up? Think carefully about that the **observation** is for this data

Tidying #3 (1/2)

What is the “observation” (a **day** or a stock on a day)?

```
mkt_untidy %>%  
  gather(day, price, starts_with('d')) %>% # wide to long  
  spread(stock, price) %>% # long back to wide-ish  
  mutate(day = gsub('d', '', day)) %>% # remove "d"  
  unite(date, year, month, day, sep = '-') %>% # 3 cols to 1  
  mutate(date = lubridate::ymd(date))
```

```
## # A tibble: 4 x 5  
##   date          CAC    DAX  FTSE   SMI  
##   <date>      <dbl> <dbl> <dbl> <dbl>  
## 1 2000-01-01 1773. 1629. 2444. 1678.  
## 2 2000-01-02 1750. 1614. 2460. 1688.  
## 3 2000-01-03 1718  1607. 2448. 1679.  
## # ... with 1 more row
```

Tidying #3 (2/2)

What is the “observation” (a day or a **stock on a day**)?

```
mkt_untidy %>%  
  gather(day, price, starts_with('d')) %>% # wide to long  
  # spread(stock, price) %>% # long back to wide-ish  
  mutate(day = gsub('d', '', day)) %>% # remove "d"  
  unite(date, year, month, day, sep = '-') %>% # 3 cols to 1  
  mutate(date = lubridate::ymd(date))
```

```
## # A tibble: 16 x 3  
##   date      stock price  
##   <date>    <chr> <dbl>  
## 1 2000-01-01 CAC    1773.  
## 2 2000-01-01 DAX    1629.  
## 3 2000-01-01 FTSE   2444.  
## # ... with 13 more rows
```

4. Multiple types of observational units are stored in the same table

This is one that gets violated a lot. Our desire is to have *all* the data in one spot.

Data should be **normalized** during the process of tidying, it is not until we reach the analytical part of our data science process that denormalization should be preferred.

golfer	birth_date	birth_place	tournament_date	tournament	final_score
Tiger Woods	1975-12-30	Cypress, CA	1996-10-06	Las Vegas	-27
Tiger Woods	1975-12-30	Cypress, CA	1996-10-20	Disney	-21
Tiger Woods	1975-12-30	Cypress, CA	1997-01-12	Mercedes	-14
Tiger Woods	1975-12-30	Cypress, CA	1997-04-13	Masters	-18

How would you tidy up?

Tidying #4 (use `dplyr::select`)

```
# helper function
select_distinct <- function(data, ...){
  select(data, ...) %>%
    distinct()
}

# golfer table
golfer <- tw_data %>%
  select_distinct(golfer, birth_date, birth_place)

# tournament table
tournament <- tw_data %>%
  select_distinct(tournament, tournament_date)

# result table
tournament_results <- tw_data %>%
  select_distinct(tournament, winner = golfer, final_score)
```

5. A single observational unit is stored in multiple tables

Have you ever worked with US government data before?



5. A single observational unit is stored in multiple tables

Have you ever worked with US government data before? If so, you know this is common:

year	cpi	year	cpi	year	cpi
2015	237	2016	240	2017	245

Not hard to remedy, but still annoying and potentially dangerous. Easy fix for *consistent* tables: `dplyr::bind_rows`

```
bind_rows(t_15, t_16, t_17)
```

```
## # A tibble: 3 x 2
##   year    cpi
##   <dbl> <dbl>
## 1  2015   237
## 2  2016   240
## 3  2017   245
```

An Aside: Displaying tidy data

How can we make it easier to scan raw values in a data table?

- Determine the roles of variables in your analysis (fixed by design of experiment vs. measured during course of experiment)
- Fixed variables should come first, then measured variables
- Order from L-R by degree of fixed-ness. The “most fixed” variables are the key describers of an observation, and are useful when we’re trying to scan values.
- Put related variables next to each other

Using this scheme, we can order rows based on the first variable and then breaking ties with the second and subsequent (fixed) variables after that.

OPTIONAL - Organizing data in spreadsheets

Conclusion

Four most important things to remember

1. Put each dataset in a table

Four most important things to remember

1. Put each dataset in a table

- `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)

Four most important things to remember

1. Put each dataset in a table

- `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
- `tibble` (AKA the nice version of `data.frame`)

Four most important things to remember

1. Put each dataset in a table
 - `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
 - `tibble` (AKA the nice version of `data.frame`)
2. Put each variable in a column

Four most important things to remember

1. Put each dataset in a table
 - `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
 - `tibble` (AKA the nice version of `data.frame`)
2. Put each variable in a column
3. Ask yourself the following questions

Four most important things to remember

1. Put each dataset in a table
 - `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
 - `tibble` (AKA the nice version of `data.frame`)
2. Put each variable in a column
3. Ask yourself the following questions
 - What are the rows of my dataset (observation, level of detail)?

Four most important things to remember

1. Put each dataset in a table
 - `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
 - `tibble` (AKA the nice version of `data.frame`)
2. Put each variable in a column
3. Ask yourself the following questions
 - What are the rows of my dataset (observation, level of detail)?
 - Is each column a *distinct* variable?

Four most important things to remember

1. Put each dataset in a table
 - `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
 - `tibble` (AKA the nice version of `data.frame`)
2. Put each variable in a column
3. Ask yourself the following questions
 - What are the rows of my dataset (observation, level of detail)?
 - Is each column a *distinct* variable?
 - How hard would it be to calculate a grouped aggregation?

Four most important things to remember

1. Put each dataset in a table
 - `data.frame` (stringsAsFactors? printing to a console? lazy evaluation?)
 - `tibble` (AKA the nice version of `data.frame`)
2. Put each variable in a column
3. Ask yourself the following questions
 - What are the rows of my dataset (observation, level of detail)?
 - Is each column a *distinct* variable?
 - How hard would it be to calculate a grouped aggregation?
4. Structure and tidy up your data to be manipulated by a computer. Ignore urges to make it easily viewed by a human.

Wrapping up

- Code is for *humans*, data is for *computers* ([relevant tweet from Vince Buffalo](#))

Wrapping up

- Code is for *humans*, data is for *computers* ([relevant tweet from Vince Buffalo](#))
- Be consciously aware of your **values**, **variables**, and **observations**

Wrapping up

- Code is for *humans*, data is for *computers* ([relevant tweet from Vince Buffalo](#))
- Be consciously aware of your **values**, **variables**, and **observations**
- Normalization can be your friend

Wrapping up

- Code is for *humans*, data is for *computers* ([relevant tweet from Vince Buffalo](#))
- Be consciously aware of your **values**, **variables**, and **observations**
- Normalization can be your friend
- Be assertive and understanding

Other resources

There's a bevy of resources I consulted for this presentation. I've arranged these in descending order of importance.

- *The tidy data paper*
- Informal version of tidy data paper
- Practical introduction to tidy data
- Data Organization in Spreadsheets
- Tidy data presentation
- Tidy data analysis (an extension of the tidy data paradigm)
- Tidy Data in Python
- Database Normalization
- Codd's 3rd Normal Form

Here's [the link to my GitHub repository](#).

Questions?

Thanks for listening!