

Taming and Tidying your Data

Class #9 / GEOG 215

Intro To Spatial Data Science

Today's Class

The Fun Part

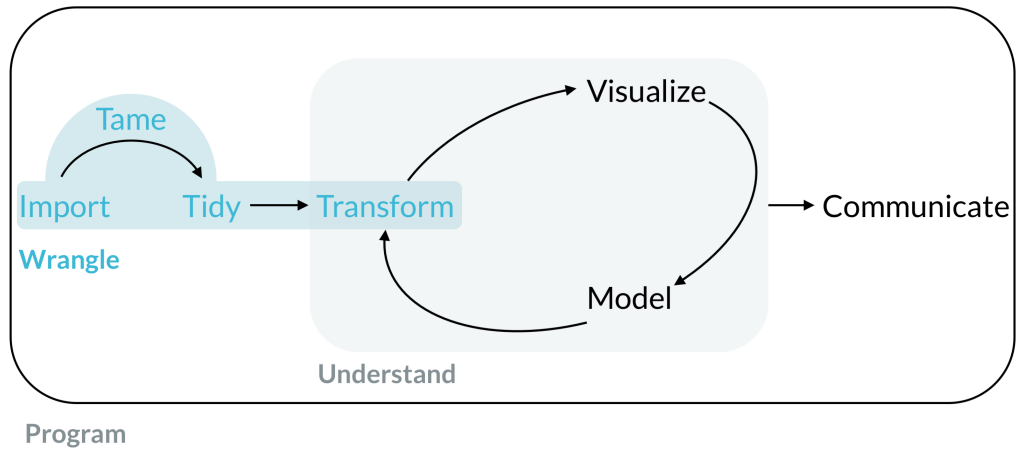
Today's Class

The Fun Part (Almost)

- Taming --> Tidying --> Transforming

Next class

- Visualize
- Explore
- Repeat



Taming Your Data

Parsing/Casting your columns

- Making sure data is in the correct format
 - Categories are factors/character
 - Quantitative variables are numeric
 - Dates are dates
- Commands from **readr** package
 - parse eg. `parse_number()`
 - casting eg. `col_number()`

Taming Your Data

Recoding Values

- Making sure values in columns are correct
 - eg. Yes = 1, No = 0
- Switch from continuous to discrete
 - eg. Changing Income values to high,medium,low
- Useful to create dummy variables (0,1) (absence/presence)
- Commands from **dplyr** package
 - parse eg. **recode** to factor using **recode_factor()**
 - frequently within **mutate**

Taming Your Data

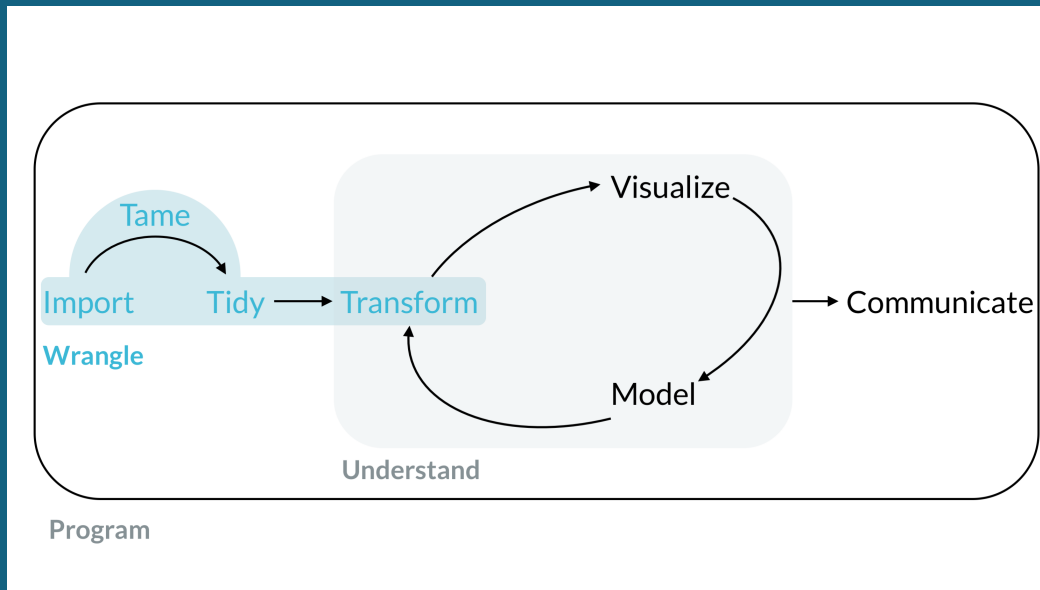
Selecting columns

- Making sure only relevant columns are included in dataset
 - eg. drop irrelevant/intermediate columns
- Make sure columns are in correct order
 - eg. Eg - all grouping columns together, all thematic columns together
- Useful to create dummy variables (0,1) (absence/presence)
- Commands from **dplyr** package
 - select eg. `select` function
 - reorder variables using `select` and helper functions

Taming Your Data

Reformatting and Renaming Variable Names

- Makes sure variable names make sense
 - eg. Total cases of disease vs percent of population with disease is reflected in column names
- variable names are consistent
 - eg. No foreign characters, consistent cases, no spaces etc
- Commands from **dplyr** and **janitor** package
 - clean variable names using `clean_names` from **janitor** package
 - rename using `rename` from **dplyr**. often used with `select` for reordering and keeping new variables



tame data \neq tidy data

Tidy Data

“Happy families are all alike; every unhappy family is unhappy in its own way.”

-- Leo Tolstoy

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

-- Hadley Wickham (inventor of Tidyverse)

Three Cardinal Rules of a tidy dataset

- Each variable must be its own column
- Each observation must have its own row
- Each value must have its own cell

country	year	cases	population
Afghanistan	1999	18	1544071
Afghanistan	2000	2666	20035360
Brazil	1999	31737	17206362
Brazil	2000	84888	17404898
China	1999	211258	1272015272
China	2000	210766	128501583

country	year	cases	population
Afghanistan	1999	18	1544071
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variables

country	year	cases	population
Afghanistan	1999	18	1544071
Afghanistan	2000	2666	20035360
Brazil	1999	31737	17206362
Brazil	2000	84888	17404898
China	1999	211258	1272015272
China	2000	210766	128501583

observations

country	year	cases	population
Afghanistan	1999	18	1544071
Afghanistan	2000	2666	20035360
Brazil	1999	31737	17206362
Brazil	2000	84888	17404898
China	1999	211258	1272015272
China	2000	210766	128501583

values

Figure 12.1: Following three rules makes a dataset tidy: variables are in columns, observations are in rows, and values are in cells.

Put each dataset in a tibble (or data frame)

Put each variable in a column

Which one out of these is tidy:

```
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
```

Making data Tidy

`pivot_longer()`

- Wide format to long format
- succeeds `gather()`

```
table4a %>%  
  pivot_longer(c(`1999`, `2000`), names_to = "year", values_to = "cases")
```

The diagram illustrates the transformation of a wide-format table (table4) into a long-format table (table4a) using the `pivot_longer()` function. The wide-format table has columns for country, 1999, and 2000. The long-format table has columns for country, year, and cases. Arrows show the mapping: the 'country' column remains the same, the '1999' and '2000' columns are mapped to the 'year' column, and the values from these columns are mapped to the 'cases' column.

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

Figure 12.2: Pivoting `table4` into a longer, tidy form.

Making data Tidy

`pivot_wider()`

- long format to wide format
- succeeds `spread()`


```
table4a %>%  
  pivot_wider(c(`1999`, `2000`), names_to = "year", values_to = "cases")
```

Making data Tidy

separate()

- *break up single column to multiple columns*
- To ensure that each value is its *own* cell

```
table3 %>%  
  separate(rate, into = c("cases", "population"), convert = TRUE)
```



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 12.4: Separating `table3` makes it tidy

Another untidy table

```
#> # A tibble: 6 x 4
#>   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
```


Making data Tidy

unite()

- *Combines multiple columns into a single column*
- To ensure that each value is its *own* cell

```
table5 %>%  
  unite(new, century, year, sep = " ")
```



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	0	2666 / 20595360
Brazil	19	99	37737 / 172006362
Brazil	20	0	80488 / 174504898
China	19	99	212258 / 1272915272
China	20	0	213766 / 1280428583

table6

Figure 12.5: Uniting `table5` makes it tidy

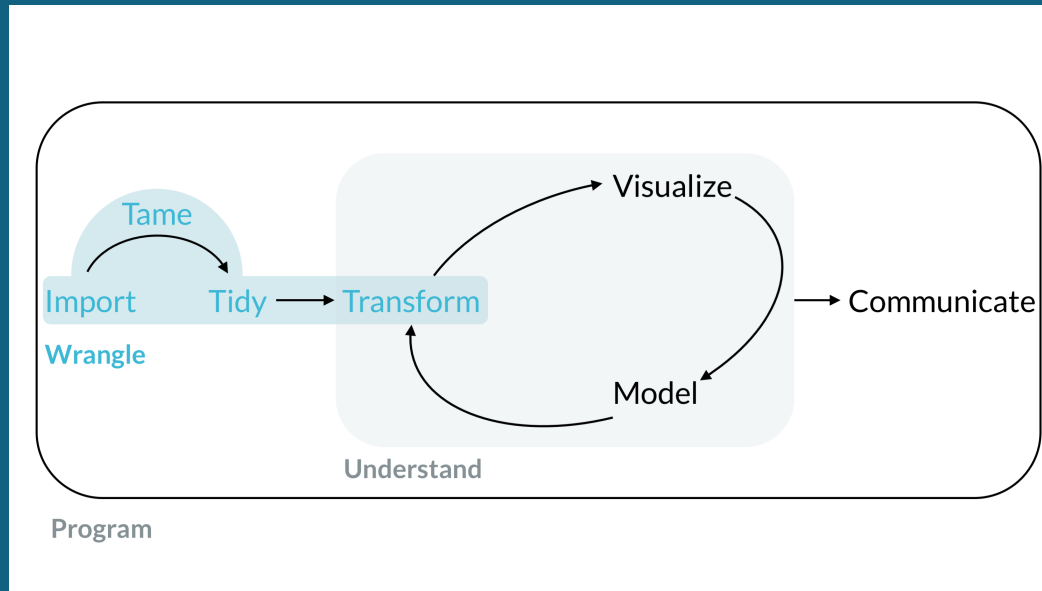
Tidy Data Tips

Tidy data is the start of your data wrangling journey, not the end

- There is not a single “tidy” version of a dataset

Not all non-tidy is incorrect, bad, or not-useful

- May have better space or performance advantages
 - Eg. Big issue with spatial data (sometimes)
- Some fields/data have their own useful conventions
- All data can be fit in rectangular structures
 - genomic data
 - Corpus of texts
 - Network/graph datasets



TRANSFORMING DATA

The famous 5 verbs of dplyr

- `arrange`
- `select`
- `filter`
- `mutate`
- `summarize`

Other important transformation variables

- `group_by()` , `ungroup`
 - often used with the famous 5
- `join` commands
 - combining multiple datasets/tables

Use cheatsheets often

<https://rstudio.com/resources/cheatsheets/>

Next Class

- Data Visualization (spatial and non-spatial)
 - email a few visualizations, we will scrutinize them
- Lab 3/HW 1 doubts
- Fill in polleverywhere Area of interest survey (LAST CHANCE)

