Data Science Concepts and Analysis

Week 1: Tidy and Transform

- Why tidy?
- Principles of tidy data
- Transforming tidy data

This week

- **Why tidy?**
    - Many ways to structure a dataset
    - Few organizational constraints 'in the wild'
- **Principles of tidy data: matching semantics with structure**
    - Data semantics: observations and variables
    - Tabular structure: rows and columns
    - The tidy standard
    - Common messes
    - Tidying operations
- **Transforming tidy data**
    - Subsetting (slicing and filtering)
    - Derived variables
    - Aggregation and summary statistics

Why tidy?

- Many possible layouts for tabular data
- 'Real' datasets have few organizational constraints

Most data are stored in tables, but **there are always multiple possible tabular layouts for the same underlying data**.

Many layouts

Let's look at some examples.

Mammal data: long layouts

Below is the Allison 1976 mammal brain-body weight dataset from week 0 lecture shown in two 'long' layouts:

In [3]:

```
mammal1.head(4)
```

Out[3]:

	body_wt	brain_wt
species		
Africanelephant	6654.000	5712.0
Africangiantpouchedrat	1.000	6.6
ArcticFox	3.385	44.5
Arcticgroundsquirrel	0.920	5.7

In [4]:

```
mammal2.head(4)
```

Out[4]:

	measurement	weight
species		
Africanelephant	brain_wt	5712.0
Africanelephant	body_wt	6654.0
Africangiantpouchedrat	brain_wt	6.6
Africangiantpouchedrat	body_wt	1.0

Many layouts

Mammal data: wide layout

Here's a third possible layout for the mammal brain-body weight data:

In [5]:

```
mammal3.iloc[:, 0:4].head()
```

Out[5]:

species	Africanelephant	Africangiantpouchedrat	ArcticFox	Arcticgroundsquirrel
measurement				
body_wt	6654.0	1.0	3.385	0.92
brain_wt	5712.0	6.6	44.500	5.70

Many layouts

GDP growth data: wide layout

Here's another example: World Bank data on annual GDP growth for 264 countries from 1961 -- 2019. The raw layout is shown below.

In [6]:

```
gdp1 = pd.read_csv('data/annual_growth.csv', encoding = 'latin1')
gdp1.head()
```

Out[6]:

	Country Name	Country Code	1961	1962	1963	1964	1965	1966	1967	1968	...	2010	2011	
0	Aruba	ABW	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	-3.685029	3.446055	-1.36986
1	Afghanistan	AFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	14.362441	0.426355	12.75228
2	Angola	AGO	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	4.403933	3.471976	8.54218
3	Albania	ALB	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	3.706892	2.545322	1.41752
4	Andorra	AND	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	-1.974958	-0.008070	-4.97444

5 rows × 61 columns

Many layouts

GDP growth data: long layout

Here's an alternative layout for the annual GDP growth data:

In [8]:

```
gdp2
```

Out[8]:

	year	growth_pct
Country Name		
Afghanistan	1961	NaN
Albania	1961	NaN
Algeria	1961	-13.605441
American Samoa	1961	NaN
Andorra	1961	NaN
...	...	...
West Bank and Gaza	2019	0.949014
World	2019	2.343378
Yemen, Rep.	2019	2.097414
Zambia	2019	1.441785
Zimbabwe	2019	-8.100000

15576 rows × 2 columns

Many layouts

SB weather data: long layouts

A third example: daily minimum and maximum temperatures recorded at Santa Barbara Municipal Airport from January 2021 through March 2021.

In [10]:

```
weather1.head()
```

Out[10]:

	STATION	NAME	DATE	TMAX	TMIN
0	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/1/2021	65	37
1	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/2/2021	62	38
2	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/3/2021	60	42
3	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/4/2021	72	43
4	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/5/2021	61	40

In [11]:

```
weather2.head()
```

Out[11]:

	STATION	TMAX	TMIN	MONTH	DAY	YEAR
0	USW00023190	65	37	1	1	2021
1	USW00023190	62	38	1	2	2021
2	USW00023190	60	42	1	3	2021
3	USW00023190	72	43	1	4	2021
4	USW00023190	61	40	1	5	2021

Many layouts

SB weather data: wide layout

Here's a wide layout for the SB weather data:

In [12]:

```
weather3.head()
```

Out[12]:

	DAY	1	2	3	4	5	6	7	8	9	10	...	22	23	24	25	26	27
MONTH	**type**																	
1	TMAX	65.0	62.0	60.0	72.0	61.0	71.0	73.0	79.0	71.0	67.0	...	61.0	59.0	65.0	55.0	57.0	54.0
	TMIN	37.0	38.0	42.0	43.0	40.0	39.0	38.0	36.0	39.0	37.0	...	41.0	40.0	38.0	44.0	40.0	48.0
2	TMAX	66.0	67.0	69.0	63.0	66.0	68.0	60.0	57.0	59.0	61.0	...	75.0	75.0	70.0	66.0	69.0	76.0
	TMIN	45.0	40.0	44.0	37.0	38.0	38.0	38.0	49.0	49.0	41.0	...	37.0	39.0	41.0	39.0	36.0	43.0
3	TMAX	68.0	66.0	59.0	62.0	67.0	69.0	60.0	69.0	65.0	58.0	...	71.0	72.0	67.0	65.0	63.0	72.0

5 rows × 31 columns

Many layouts

UN development data: multiple tables

A final example: United Nations country development data organized into different tables according to variable type.

Here is a table of population measurements:

In [14]:

```
undev1.head(3)
```

Out[14]:

	total_pop	urban_pct_pop	pop_under5	pop_15to64	pop_over65
country					
Afghanistan	38.0	25.8	5.6	20.9	1.0
Albania	2.9	61.2	0.2	2.0	0.4
Algeria	43.1	73.2	5.0	27.1	2.8

And here is a table of a few gender-related variables:

In [15]:

```
undev2.head(3)
```

Out[15]:

	gender_inequality	parliament_pct_women	labor_participation_women	labor_participation_men
country				
Norway	0.045	40.8	60.4	67.2
Ireland	0.093	24.3	56.0	68.4
Switzerland	0.025	38.6	62.9	73.8

Many layouts

UN development data: one table

Here are both tables merged by country:

In [17]:

```
undev_combined1.head(3)
```

Out[17]:

	total_pop	urban_pct_pop	pop_under5	pop_15to64	pop_over65	gender_inequality	parliament_pct_women	labor_participation_women	labor_participation_men
country									
Afghanistan	38.0	25.8	5.6	20.9	1.0	0.655	27.2	21.6	74.7
Albania	2.9	61.2	0.2	2.0	0.4	0.181	29.5	46.7	64.6
Algeria	43.1	73.2	5.0	27.1	2.8	0.429	21.5	14.6	67.4

Many layouts

UN development data: one (longer) table

And here is another arrangement of the merged table:

In [19]:

```
undev_combined2.head(5)
```

Out[19]:

	gender_variable	gender_value	population_variable	population_value
country				
Afghanistan	gender_inequality	0.655	total_pop	38.0
Albania	gender_inequality	0.181	total_pop	2.9
Algeria	gender_inequality	0.429	total_pop	43.1
Andorra	gender_inequality	NaN	total_pop	0.1
Angola	gender_inequality	0.536	total_pop	31.8

Many layouts

Pause and reflect
Return to one of the examples and review the different layouts.

- If you had to pick one layout, which would you choose?
- Why would you choose that one?
    - Aesthetic preference?
    - "Just makes sense this way"?
    - "This way is better because..."?
- Can you envision advantages or disadvantages to different layouts?

Few organizational constraints

It's surprisingly difficult to articulate reasons why one layout might be preferable to another.

Possibly for this reason, most data are stored in a layout that made intuitive sense to someone responsible for data management or collection at some point in time.

- Usually the choice of layout isn't principled
- Idiosyncratic: two people are likely to make different choices

As a result:

- Few widely used conventions
- Lots of variability 'in the wild'
- Datasets are often organized in bizarre ways

Consequences for the data scientist

Because of the wide range of possible layouts for a dataset, and the variety of choices that are made about how to store data, **data scientists are constantly faced with determining how best to reorganize datasets in a way that facilitates exploration and analysis.**

Broadly, this involves two interdependent choices:

- *Choice of **representation**: how to encode information.*
    - Example: parse dates as 'MM/DD/YYYY' (one variable) or 'MM', 'DD', 'YYYY' (three variables)?
    - Example: use values 1, 2, 3 or 'low', 'med', 'high'?
    - Example: name variables 'question1', 'question2', ..., or 'age', 'income', ...?
- *Choice of **form**: how to display information*
    - Example: wide table or long table?
    - Example: one table or many?

Remedy: the tidy data standard

Instead of addressing these challenges -- choice of form and representation -- anew every single time, it is immensely helpful to have a set of organizational principles to standardize the process of rearranging data.

The **tidy data standard** is a principled way of organizing data values. It has two main advantages:

1. Facilitates workflow by establishing a consistent dataset structure.
2. Principles are designed to make transformation, exploration, visualization, and modeling easy.

This is a pretty intuitive idea. Many (most?) other things are easier when they're thoughtfully organized:

- Kitchens
- Closets
- Taxes

Principles of tidy data

- **Tidy data matches semantics with structure**
  - Data semantics: observations, variables, units
  - Tabular structure: rows and columns
  - The tidy data standard
  - Common messes
  - Tidying operations

Matching semantics with structure

> *"Tidying your data means storing it in a consistent form that matches the semantics of the dataset with the way it is stored. In brief, when your data is tidy, each column is a variable, and each row is an observation. Tidy data is important because the consistent structure lets you focus your struggle on questions about the data, not fighting to get the data into the right form for different functions." Wickham and Grolemund, R for Data Science, 2017.*

A dataset is a collection of values.

- semantics: meaning
    - *data semantics* refers to the meaning of each value
- structure: form
    - *data structure* refers to how values are arranged

The **tidy standard**: data semantics ↔ data structure

Data semantics: units, variables, and observations

Data semantics refers to the meaning of values. To introduce some general vocabulary, each value is

- an **observation**
- of a **variable**
- taken on a **unit**.

To be precise:

- An **observational unit** is the entity measured.
- A **variable** is an attribute measured on each unit.
- An **observation** is a collection of measurements taken on one unit.

Identifying units, variables, and observations

Let's do an example. In the GDP growth data:

Term	Definition	Example
Observational units	Entity measured	Countries
Variables	Attributes measured	Year, GDP growth
Observations	Set of measurements per unit	Annual records

In [20]:

```
# third record
gdp2.iloc[[2], :]
```

Out[20]:

	year	growth_pct
Country Name		
Algeria	1961	-13.605441

So, below, -13.605441 (variable) in 1961 (variable) is a record (observation) for Algeria (unit).

Identifying units, variables, and observations

In the weather data:

Term	Definition	Instance
Observational unit	Entity measured	SB airport weather station (location)
Variables	Attributes measured	Min temp, max temp, date, station info
Observations	Set of measurements per unit	Daily records

In [21]:

```
# first record
weather1.iloc[[0], :]
```

Out[21]:

	STATION	NAME	DATE	TMAX	TMIN
0	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/1/2021	65	37

For example: 65 degrees Farenheit is the maximum temperature (one variable) recorded on a day (one observation) at the SB airport weather station (unit).

Data structure

Data structure refers to the form in which it is stored.
In this context, that means a tabular arranement of a dataset comprising:

- rows
- columns

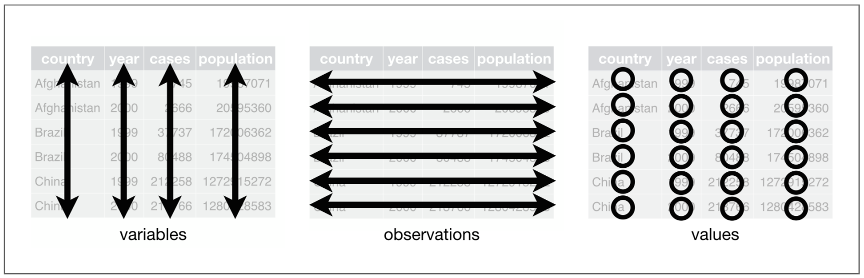
As we saw, there are multiple structures available to represent any dataset.

The tidy standard

The tidy standard consists in matching semantics and structure.

We can now make that precise. A dataset conforming to the **tidy standard** is organized so that:

1. Each variable is a column.
2. Each observation is a row.
3. Each table contains measurements on only one type of observational unit.



Tidy or messy?

Let's revisit some of our examples of multiple layouts, starting with `gdp1`.

In [22]:

```
gdp1.head(3)
```

Out[22]:

	Country Name	Country Code	1961	1962	1963	1964	1965	1966	1967	1968	...	2010	2011	20
0	Aruba	ABW	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	-3.685029	3.446055	-1.36986
1	Afghanistan	AFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	14.362441	0.426355	12.75228
2	Angola	AGO	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	4.403933	3.471976	8.54218

3 rows × 61 columns

We can compare the semantics and structure for alignment:

Semantics	-	Structure	-
Observations	Annual records	Rows	Countries
Variables	GDP growth and year	Columns	Value of year
Observational units	Countries	Tables	Just one

Rules 1 and 2 are violated, since column names are values, not variables. *Not tidy*.

Tidy or messy?

In `gdp2`:

In [23]:

```
gdp2.head(4)
```

Out[23]:

	year	growth_pct
Country Name		
Afghanistan	1961	NaN
Albania	1961	NaN
Algeria	1961	-13.605441
American Samoa	1961	NaN

We can compare the semantics and structure for alignment:

Semantics	-	Structure	-
Observations	Annual records	Rows	Annual records
Variables	GDP growth and year	Columns	GDP growth and year
Observational units	Countries	Tables	Just one

All three rules are met: rows are observations, columns are variables, and there's one unit type and one table. *Tidy*.

Tidy or messy?

In `weather1`:

In [24]:

```
weather1.head(3)
```

Out[24]:

	STATION	NAME	DATE	TMAX	TMIN
0	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/1/2021	65	37
1	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/2/2021	62	38
2	USW00023190	SANTA BARBARA MUNICIPAL AIRPORT, CA US	1/3/2021	60	42

We can compare the semantics and structure for alignment:

Semantics	-	Structure	-
Observations	Daily records	Rows	Daily records
Variables	Min temp, max temp, date	Columns	Min temp, max temp, date, and station info
Observational units	Weather stations	Tables	Just one

All three rules are met: rows are observations, columns are variables, and there's one unit type and one table. *Tidy*.

Tidy or messy?

In `weather3`:

In [25]:

```
weather3
```

Out[25]:

	DAY	1	2	3	4	5	6	7	8	9	10	...	22	23	24	25	26	27
MONTH	type																	
1	TMAX	65.0	62.0	60.0	72.0	61.0	71.0	73.0	79.0	71.0	67.0	...	61.0	59.0	65.0	55.0	57.0	54.0
	TMIN	37.0	38.0	42.0	43.0	40.0	39.0	38.0	36.0	39.0	37.0	...	41.0	40.0	38.0	44.0	40.0	48.0
2	TMAX	66.0	67.0	69.0	63.0	66.0	68.0	60.0	57.0	59.0	61.0	...	75.0	75.0	70.0	66.0	69.0	76.0
	TMIN	45.0	40.0	44.0	37.0	38.0	38.0	38.0	49.0	49.0	41.0	...	37.0	39.0	41.0	39.0	36.0	43.0
3	TMAX	68.0	66.0	59.0	62.0	67.0	69.0	60.0	69.0	65.0	58.0	...	71.0	72.0	67.0	65.0	63.0	72.0
	TMIN	37.0	36.0	36.0	37.0	39.0	43.0	47.0	47.0	47.0	43.0	...	50.0	49.0	41.0	44.0	40.0	41.0

6 rows × 31 columns

We can compare the semantics and structure for alignment:

Semantics	-	Structure	-
Observations	Daily records	Rows	Month and measurement type
Variables	Min temp, max temp, date	Columns	Day of month
Observational units	Weather stations	Tables	Just one

This violates both rules 1 and 2, since values are stored as both rows and columns. *Not tidy*.

Tidy or messy?

In `undev1` and `undev2`:

In [26]:

```
undev1.head(2)
```

Out[26]:

	total_pop	urban_pct_pop	pop_under5	pop_15to64	pop_over65
country					
Afghanistan	38.0	25.8	5.6	20.9	1.0
Albania	2.9	61.2	0.2	2.0	0.4

In [27]:

```
undev2.head(2)
```

Out[27]:

	gender_inequality	parliament_pct_women	labor_participation_women	labor_participation_men
country				
Norway	0.045	40.8	60.4	67.2
Ireland	0.093	24.3	56.0	68.4

We can compare the semantics and structure for alignment:

Semantics	-	Structure	-
Observations	Country records	Rows	Country records
Variables	Gender-related and population measurements	Columns	Gender-related and population measurements
Observational units	Countries	Tables	One per variable type

This violates rule 3 -- there is only one observational unit, but multiple tables. *Not tidy*.

Common messes

> *"Well, here's another nice mess you've gotten me into"* -- *Oliver Hardy*

These examples illustrate some of the most common kinds of messiness:

- *Columns are values, not variables*
    - GDP data `gdp1`: columns are 1961, 1962, ...
- *Multiple variables are stored in one column*
    - Mammal data `mammal2`: weight column contains both body and brain weights
- *Variables or values are stored in rows and columns*
    - Weather data `weather3`: date values are stored in rows and columns, each column contains both min and max temperatures
- *Measurements on one type of observational unit are divided into multiple tables.*
    - UN development data: `undev1` stores population variables; `undev2` stores gender-related variables.

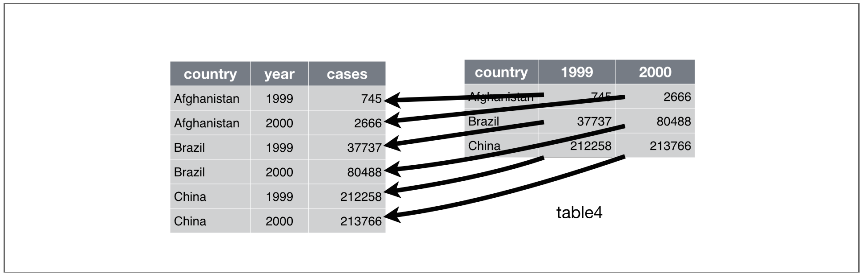
Tidying operations

These common messes can be cleaned up by some simple operations:

- *melt*
    - reshape a dataframe from wide to long format
- *pivot*
    - reshape a dataframe from long to wide format
- *merge*
    - combine two dataframes row-wise by matching the values of certain columns

Melt

Melting resolves the problem of having values stored as columns (common mess 1).



Melt

To illustrate with `gdp1`:

In [28]:

```
gdp1.head(3)
```

Out[28]:

	Country Name	Country Code	1961	1962	1963	1964	1965	1966	1967	1968	...	2010	2011	20
0	Aruba	ABW	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	-3.685029	3.446055	-1.36986
1	Afghanistan	AFG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	14.362441	0.426355	12.75228
2	Angola	AGO	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	4.403933	3.471976	8.54218

3 rows × 61 columns

In [29]:

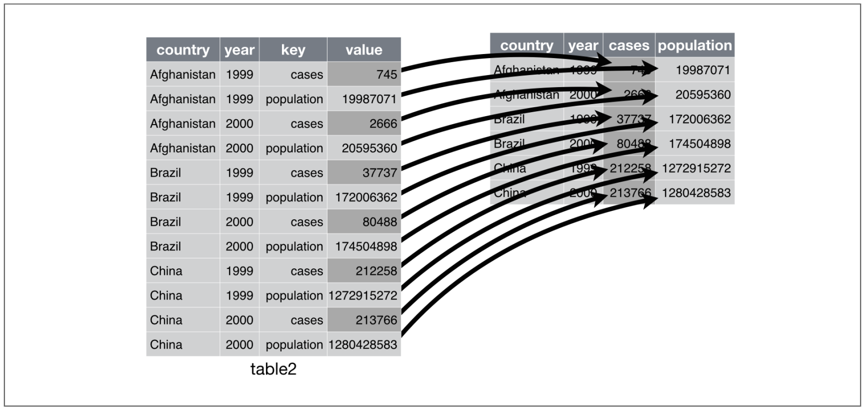
```
gdp1.melt(
    id_vars = ['Country Name', 'Country Code'], # which variables do you want to retain for each row? .
    var_name = 'Year', # what do you want to name the variable that will contain the column names?
    value_name = 'GDP Growth', # what do you want to name the variable that will contain the values?
).head()
```

Out[29]:

	Country Name	Country Code	Year	GDP Growth
0	Aruba	ABW	1961	NaN
1	Afghanistan	AFG	1961	NaN
2	Angola	AGO	1961	NaN
3	Albania	ALB	1961	NaN
4	Andorra	AND	1961	NaN

Pivot

Pivoting resolves the issue of having multiple variables stored in one column (common mess 2).



Pivot

For example, the `mammal2` layout can be put in tidier form with a pivot:

In [30]:

```
mammal2.head(3)
```

Out[30]:

	measurement	weight
species		
Africanelephant	brain_wt	5712.0
Africanelephant	body_wt	6654.0
Africangiantpouchedrat	brain_wt	6.6

In [31]:

```
mammal2.pivot(
    columns = 'measurement', # which variable(s) do you want to send to new column names?
    values = 'weight' # which variable(s) do you want to use to populate the new columns?
).head(3)
```

Out[31]:

measurement	body_wt	brain_wt
species		
Africanelephant	6654.000	5712.0
Africangiantpouchedrat	1.000	6.6
ArcticFox	3.385	44.5

Pivot and melt

Common mess 3 is a combination of messes 1 and 2: values or variables are stored in both rows and columns. Pivoting and melting in sequence can usually fix this. `weather3` illustrates this issue:

In [32]:

```
weather3
```

Out[32]:

	DAY	1	2	3	4	5	6	7	8	9	10	...	22	23	24	25	26	27
MONTH	type																	
1	TMAX	65.0	62.0	60.0	72.0	61.0	71.0	73.0	79.0	71.0	67.0	...	61.0	59.0	65.0	55.0	57.0	54.0
	TMIN	37.0	38.0	42.0	43.0	40.0	39.0	38.0	36.0	39.0	37.0	...	41.0	40.0	38.0	44.0	40.0	48.0
2	TMAX	66.0	67.0	69.0	63.0	66.0	68.0	60.0	57.0	59.0	61.0	...	75.0	75.0	70.0	66.0	69.0	76.0
	TMIN	45.0	40.0	44.0	37.0	38.0	38.0	38.0	49.0	49.0	41.0	...	37.0	39.0	41.0	39.0	36.0	43.0
3	TMAX	68.0	66.0	59.0	62.0	67.0	69.0	60.0	69.0	65.0	58.0	...	71.0	72.0	67.0	65.0	63.0	72.0
	TMIN	37.0	36.0	36.0	37.0	39.0	43.0	47.0	47.0	47.0	43.0	...	50.0	49.0	41.0	44.0	40.0	41.0

6 rows × 31 columns

Pivot and melt

Common mess 3 is a combination of messes 1 and 2: values or variables are stored in both rows and columns. Pivoting and melting in sequence can usually fix this. `weather3` illustrates this issue:

First melt

In [33]:

```
weather3.melt(
    ignore_index = False,
    var_name = 'day',
    value_name = 'temp'
).head()
```

Out[33]:

		day	temp
MONTH	**type**		
1	**TMAX**	1	65.0
	TMIN	1	37.0
2	**TMAX**	1	66.0
	TMIN	1	45.0
3	**TMAX**	1	68.0

Pivot and melt

Common mess 3 is a combination of messes 1 and 2: values or variables are stored in both rows and columns. Pivoting and melting in sequence can usually fix this. `weather3` illustrates this issue:

Then pivot

In [34]:

```
weather3.melt(
    ignore_index = False,
    var_name = 'day',
    value_name = 'temp'
).reset_index().pivot(
    index = ['MONTH', 'day'],
    columns = 'type',
    values = 'temp'
).reset_index().rename_axis(columns = {'type': ''}).head()
```

Out[34]:

	MONTH	day	TMAX	TMIN
0	1	1	65.0	37.0
1	1	2	62.0	38.0
2	1	3	60.0	42.0
3	1	4	72.0	43.0
4	1	5	61.0	40.0

Merge

Merging resolves the issue of storing observations or variables on one unit type in multiple tables (mess 4). The basic idea is to combine by matching rows.

Product (P1)	
ProductID	Name
1	Zephyr
2	Comet
3	Zephyr
4	Bomber

Product (P2)	
ProductID	Name
1	Zephyr
2	Comet
3	Zephyr
4	Bomber

P1.ProductID	P1.Name	P2.Name	P2.ProductID
1	Zephyr	Zephyr	1
1	Zephyr	Zephyr	3
2	Comet	Comet	3
3	Zephyr	Zephyr	3
3	Zephyr	Zephyr	1
4	Bomber	Bomber	4

However, there are a number of different merging rules (corresponding to SQL joins).

Merge

The code below combines columns in each table by matching rows based on country.

In [35]:

```
pd.merge(undev1, undev2, on = 'country').head(4)
```

Out[35]:

	total_pop	urban_pct_pop	pop_under5	pop_15to64	pop_over65	gender_inequality	parliament_pct_women	labor_participation_women	labor_participation_men
country									
Afghanistan	38.0	25.8	5.6	20.9	1.0	0.655	27.2	21.6	74.7
Albania	2.9	61.2	0.2	2.0	0.4	0.181	29.5	46.7	64.6
Algeria	43.1	73.2	5.0	27.1	2.8	0.429	21.5	14.6	67.4
Andorra	0.1	88.0	NaN	NaN	NaN	NaN	46.4	NaN	NaN

Merge

There are various rules for exactly how to merge, but the general syntactical procedure to merge dataframes `df1` and `df2` is this.

- Specify an **order**: `merge(df1, df2)` or `merge(df2, df1)`.
- Specify **keys**: the shared columns to use for matching rows of `df1` with rows of `df2`.
    - for example, merging on `date` will align rows in `df2` with rows of `df1` that have the same value for `date`
- Specify a **rule** for which rows to return after merging
    - keep all rows with key entries in `df1`, drop non-matching rows in `df2` ('left' join)
    - keep all rows with key entries in `df2` drop non-matching rows in `df1` ('right' join)
    - keep all rows with key entries in either `df1` or `df2`, inducing missing values ('outer' join)
    - keep all rows with key entries in both `df1` and `df2` ('inner' join)

You don't need to memorize these -- you'll learn from experience using them and can always look them up (I usually need to).

Transform

Tidying facilitates transformation.

> *"Transformation includes narrowing in on observations of interest (like all people in one city, or all data from the last year), creating new variables that are functions of existing variables (like computing speed from distance and time), and calculating a set of summary statistics (like counts or means)." Wickham and Grolemund, R for Data Science, 2017.*

For our purposes, a **transformation** is ***any operation that modifies the shape or values of a data frame***. This includes:

- Subsetting (slicing and filtering)
- Defining new variables
- Aggregation and summary statistics

You are learning transformation tools in lab 1. They're a lot easier to use if data are tidy.

Tidying facilitates transformation

Why use the tidy standard? Wouldn't any system of organization do just as well?

The tidy standard has three main advantages:

1. Having a consistent system of organization makes it easier to focus on analysis and exploration.
2. **Transformation of tidy data is especially natural in most computing environments due to vectorized operations.**
3. Many tools for exploration, visualization, and modeling are designed to work with tidy data inputs.

Subsetting

Tidy data is easier to subset (slice and filter).

If, for instance, we want to inspect population and women in parliament for Mexico and Colombia, we can retrieve those values by simply calling the corresponding observations and variables:

In [36]:

```
undev_combined1.loc[['Mexico', 'Colombia', 'United States'], ['total_pop', 'parliament_pct_women']]
```

Out[36]:

	total_pop	parliament_pct_women
country		
Mexico	127.6	48.4
Colombia	50.3	19.6
United States	329.1	23.7

Subsetting

The same goal can be achieved using a non-tidy format, but the code is more verbose and the output is less interpretable.

In [37]:

```
undev_combined2[
    (undev_combined2.population_variable == 'total_pop') &
    (undev_combined2.gender_variable == 'parliament_pct_women')
].loc[['Mexico', 'Colombia', 'United States'], ['population_value', 'gender_value']]
```

Out[37]:

	population_value	gender_value
country		
Mexico	127.6	48.4
Colombia	50.3	19.6
United States	329.1	23.7

Defining new variables

Vectorization of operations in pandas and numpy make tidy data especially nice to manipulate mathematically.

For example, to calculate the temperature range in a day from the Santa Barbara weather data, having the min and max temps in columns arranged by day makes this easy:

In [38]:

```
weather2['TRANGE'] = weather2.TMAX - weather2.TMIN
weather2.head()
```

Out[38]:

	STATION	TMAX	TMIN	MONTH	DAY	YEAR	TRANGE
0	USW00023190	65	37	1	1	2021	28
1	USW00023190	62	38	1	2	2021	24
2	USW00023190	60	42	1	3	2021	18
3	USW00023190	72	43	1	4	2021	29
4	USW00023190	61	40	1	5	2021	21

Defining new variables

Again, the same result could be achieved using non-tidy data, but the operation is a bit more complicated to execute and less interpretable.

In [39]:

```
weather3a = weather3.reset_index('type')
maxtemps = weather3a[weather3a.type == 'TMAX'].drop(columns = 'type')
mintemps = weather3a[weather3a.type == 'TMIN'].drop(columns = 'type')
temprange = maxtemps - mintemps
temprange
```

Out[39]:

DAY	1	2	3	4	5	6	7	8	9	10	...	22	23	24	25	26	27	
MONTH																		
1	28.0	24.0	18.0	29.0	21.0	32.0	35.0	43.0	32.0	30.0	...	20.0	19.0	27.0	11.0	17.0	6.0	6.(
2	21.0	27.0	25.0	26.0	28.0	30.0	22.0	8.0	10.0	20.0	...	38.0	36.0	29.0	27.0	33.0	33.0	30.(
3	31.0	30.0	23.0	25.0	28.0	26.0	13.0	22.0	18.0	15.0	...	21.0	23.0	26.0	21.0	23.0	31.0	32.(

3 rows × 31 columns

Aggregation and summary statistics

Vectorization similarly makes aggregations straightforward when data are tidy.

For instance, the monthly average temperatures are easy to compute from tidy weather data:

In [40]:

```
weather2.groupby('MONTH').mean().drop(columns = ['DAY', 'YEAR'])
```

Out[40]:

MONTH	TMAX	TMIN	TRANGE
1	67.645161	40.870968	26.774194
2	67.250000	41.785714	25.464286
3	65.310345	42.172414	23.137931

Aggregation and summary statistics

It's not necessarily harder to envision how to perform these operations in the non-tidy layouts; it's just trickier to execute and the output is a little less organized.

In [41]:

```
weather3.mean(axis = 1)
```

Out[41]:

```
MONTH  type
1      TMAX    67.645161
       TMIN    40.870968
2      TMAX    67.250000
       TMIN    41.785714
3      TMAX    65.310345
       TMIN    42.172414
dtype: float64
```

In [42]:

```
temprange.mean(axis = 1)
```

Out[42]:

```
MONTH
1    26.774194
2    25.464286
3    23.137931
dtype: float64
```

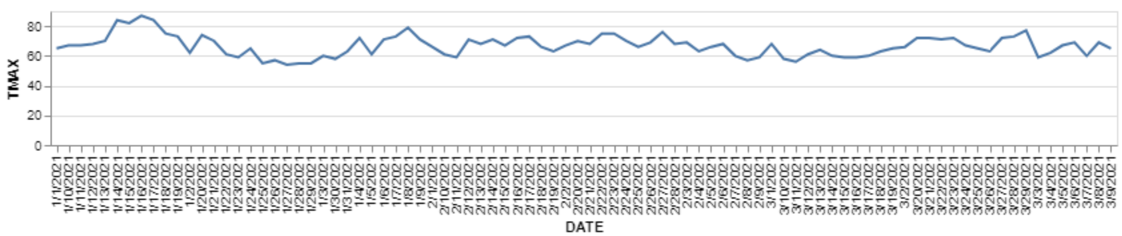
Visualization

Plotting libraries often operate in such a way that tidy data is easier to plot.

In [43]:

```
alt.Chart(weather1).mark_line().encode(
    x = 'DATE',
    y = 'TMAX'
).properties(
    width = 800,
    height = 100
)
```

Out[43]:



Exceptions

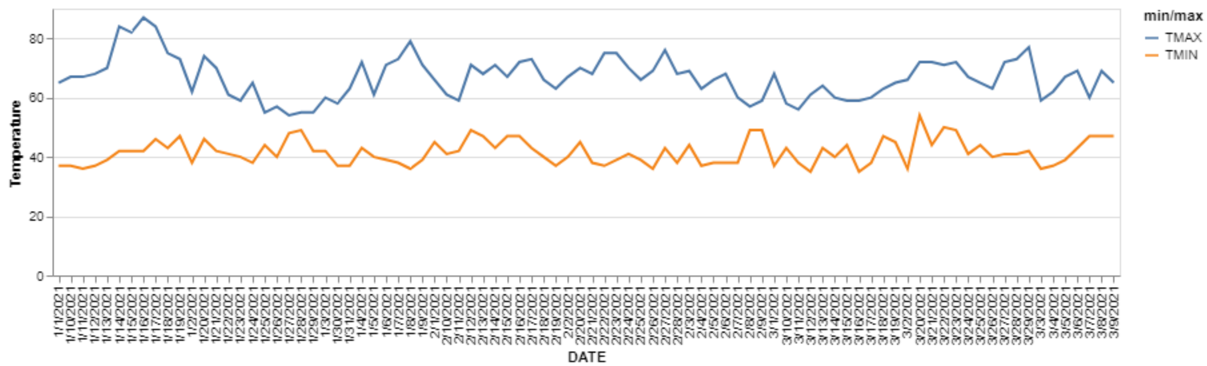
There will be situations where you'll need to deviate from this format for various purposes.

Often, plotting and table construction require reshaping data into non-tidy formats, for example:

In [45]:

```
plot
```

Out[45]:



Exceptions

There will be situations where you'll need to deviate from this format for various purposes.

That plot relied on formatting the data as follows:

In [46]:

```
weather4.head(4)
```

Out[46]:

	DATE	min/max	Temperature
0	1/1/2021	TMIN	37
1	1/2/2021	TMIN	38
2	1/3/2021	TMIN	42
3	1/4/2021	TMIN	43

Exceptions

However, even in these situations, tidy data provides a useful starting point; it is often straightforward to manipulate into non-tidy formats using the same pivot, melt, and merge operations.

For example, the plot above was created after a simple melt operation on the tidy data.

In [47]:

```
weather1.melt(
    id_vars = 'DATE',
    value_vars = ['TMIN', 'TMAX'],
    value_name = 'Temperature',
    var_name = 'min/max'
).head()
```

Out[47]:

	DATE	min/max	Temperature
0	1/1/2021	TMIN	37
1	1/2/2021	TMIN	38
2	1/3/2021	TMIN	42
3	1/4/2021	TMIN	43
4	1/5/2021	TMIN	40

Review

- In tidy data, rows and columns correspond to observations and variables.
    - This provides a standard dataset structure that facilitates exploration and analysis.
    - Many datasets are not stored in this format.
    - Most of the time in PSTAT 100, we'll give you tidy (or mostly tidy) datasets.
- Transformation operations are a lot easier with tidy data.
    - Due in part to the way tools in pandas are designed.
    - The goal of lab 1 is to learn these operations.
- There are situations where non-tidy data is useful.
    - In PSTAT100, these will usually arise in plotting and tabulation tasks.

Up next

We started *en media res* at this stage of the lifecyle (tidy) so that you could start developing skills that would enable you to jump right into playing with datasets.
Next week, we'll backtrack to the collect and acquaint stages and discuss:

- sampling;
- missing data.