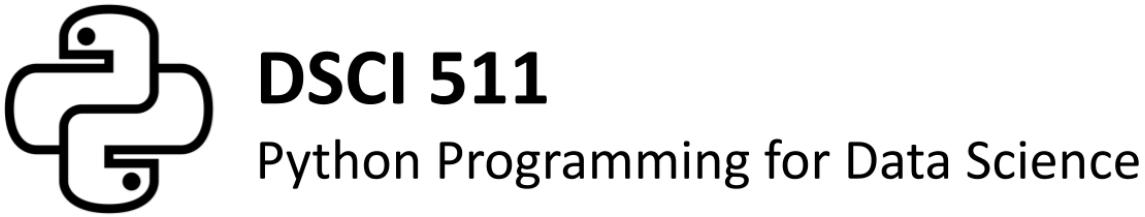
Lecture 4: Plotting, Merging and Grouping

Contents



Lecture Learning Objectives

- Make basic plots in Pandas by accessing the `.plot` attribute or importing functions from `pandas.plotting`.
- Combine dataframes using `df.merge()` and `pd.concat()` and know when to use these different methods.
- Apply functions to a dataframe or Series `DataFrame.apply()` and `DataFrame.applymap()` and `Series.map()`
- Perform grouping and aggregating operations using `df.groupby()` and `df.agg()`.
- Perform aggregating methods on grouped or ungrouped objects such as finding the minimum, maximum and sum of values in a dataframe using `df.agg()`.

```
import numpy as np
import pandas as pd
```

Visualizing your data

You will study data visualization in depth in DSCI 531. However, it is good to know that pandas provides some basic plotting functionality– you can use this to take a quick look at your data.

This feature of pandas is accessed via the `plot()` method. It uses the `matplotlib` library, which you can install with `conda install matplotlib` as you have done with other packages.

Once we have `matplotlib` installed, let's load in the dataset `'data/cycling_data.csv'` which includes some dates, times and comments about bike rides.

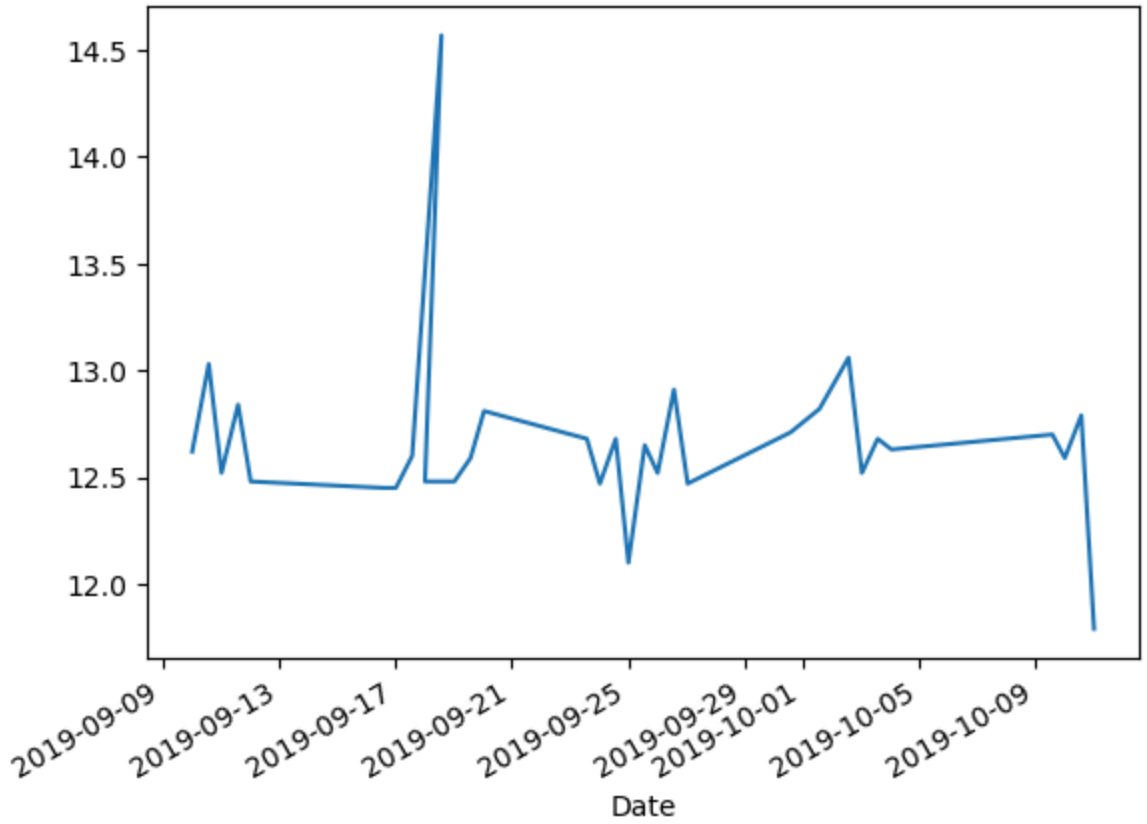
```
bike_df = pd.read_csv('data/cycling_data.csv', index_col=0, parse_dates=True).dropna()
bike_df.head()
```

Date	Name	Type	Time	Distance	Comments
2019-09-10 00:13:04	Afternoon Ride	Ride	2084	12.62	Rain
2019-09-10 13:52:18	Morning Ride	Ride	2531	13.03	rain
2019-09-11 00:23:50	Afternoon Ride	Ride	1863	12.52	Wet road but nice weather
2019-09-11 14:06:19	Morning Ride	Ride	2192	12.84	Stopped for photo of sunrise
2019-09-12 00:28:05	Afternoon Ride	Ride	1891	12.48	Tired by the end of the week

Let's go ahead and make a plot of the distances ridden.

```
bike_df['Distance'].plot()
```

```
<Axes: xlabel='Date'>
```

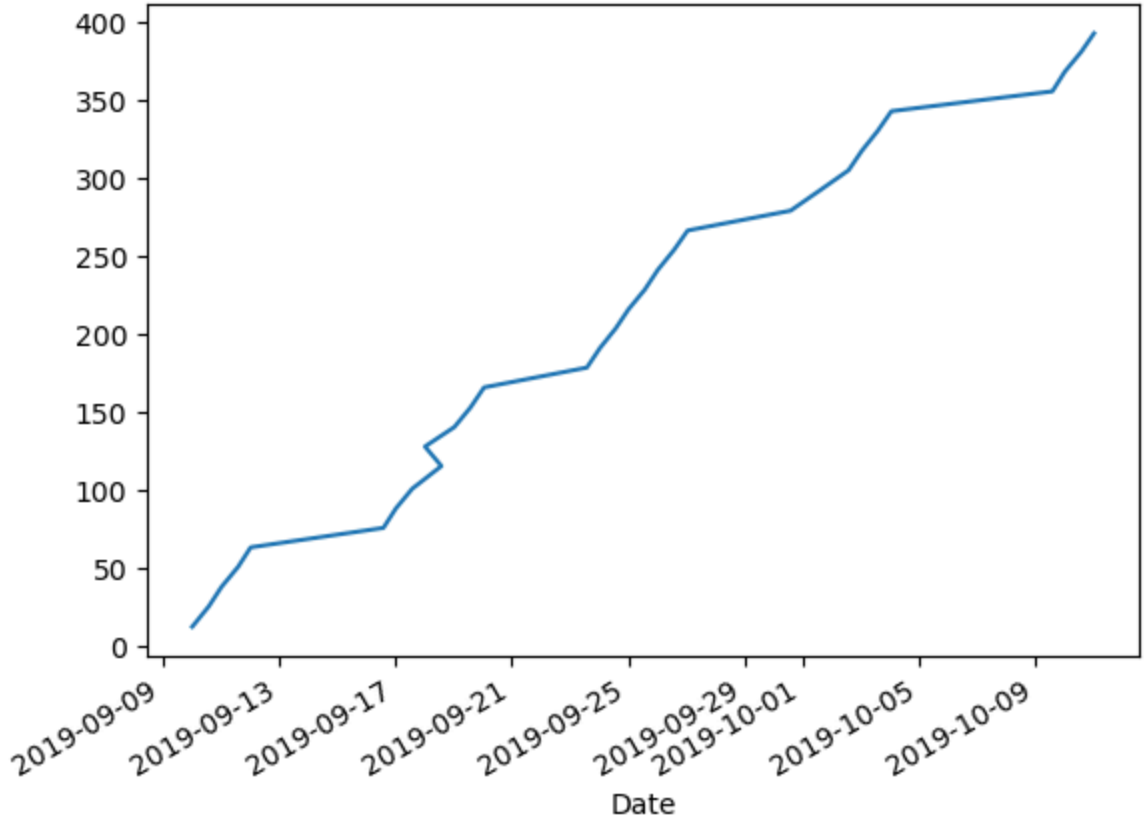


Notice the line graph joined adjacent points together, which may suggest there was a non-zero riding distance on (say) Sep 13 or Sep 21. But there are no biking entries for these days!

Plotting with pandas can be a good way to take a quick look at your data. It can also help you to spot potential problems. For example, let's make a graph of *cumulative* distance covered over time.

```
bike_df['Distance'].cumsum().plot()
```

```
<Axes: xlabel='Date'>
```



That kink in the graph is funny... since we're plotting cumulative distance, the line should always be moving up and to the right!

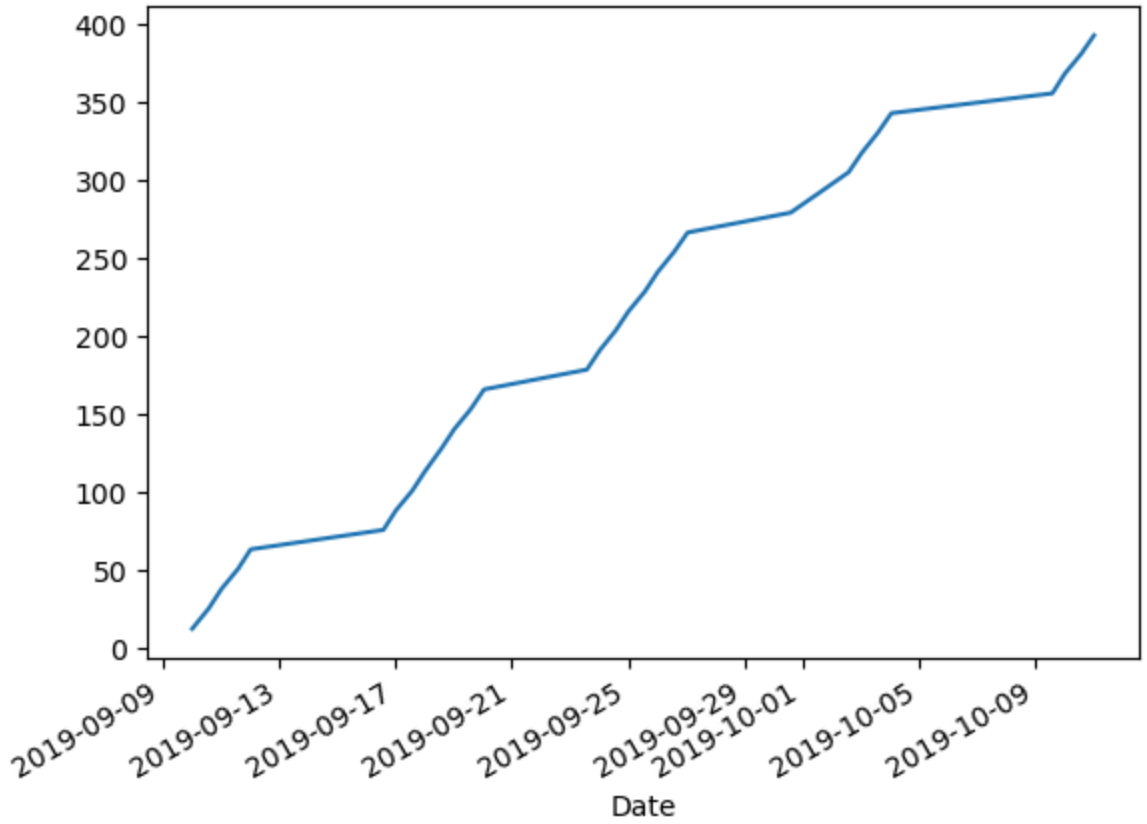
```
bike_df.loc['2019-09-18']
```

	Name	Type	Time	Distance	Comments
Date					
2019-09-18 13:49:53	Morning Ride	Ride	2903	14.57	Raining today
2019-09-18 00:15:52	Afternoon Ride	Ride	2101	12.48	Pumped up tires

Looks like some entries were out of chronological order. We should sort the index before plotting.

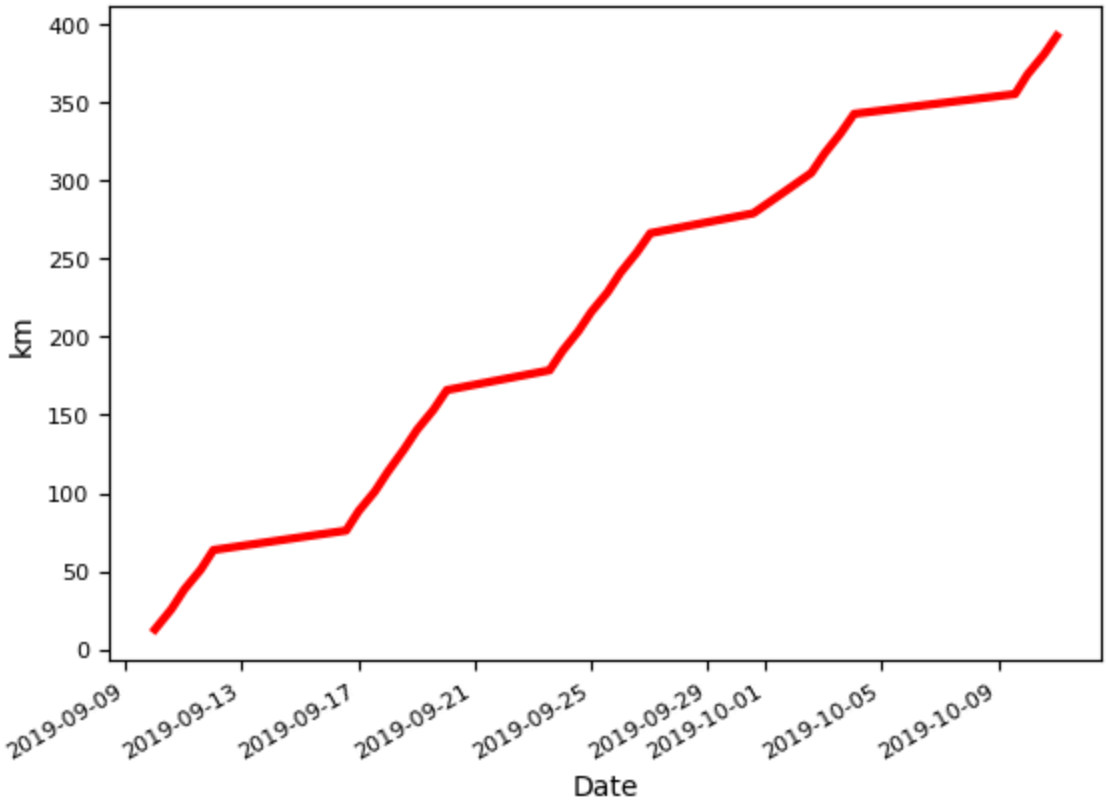
```
bike_df = bike_df.sort_index()
bike_df['Distance'].cumsum().plot()
```

```
<Axes: xlabel='Date'>
```



That's better! We can also change plot parameters like colour and line thickness.

```
bike_df['Distance'].cumsum().plot.line(fontsize=8, linewidth=3, color='r', ylabel='km');
```



There are many other kinds of plots you can make:

Method	Plot Type
`bar` or `barh`	bar plots
`hist`	histogram
`box`	boxplot
`kde` or `density`	density plots
`area`	area plots
`scatter`	scatter plots
`hexbin`	hexagonal bin plots
`pie`	pie plots

Plus, there are more advanced plotting functions (scatter matrix, lag plots and others) that can be accessed via the `pandas.plotting` module.

Combining multiple data frames

Sometimes we have meaningful data spread across different data frames (or read in from different files) that we wish to combine. There are many ways to combine data in pandas, and we will look at some of them today.

To begin let's load in some data frames with weather information for different dates. You might notice that these frames share information across certain rows or columns, i.e. the data sets are related.

```
w1 = pd.read_csv('data/weather1.csv', index_col=0)
w2 = pd.read_csv('data/weather2.csv', index_col=0)
w3 = pd.read_csv('data/weather3.csv', index_col=0)
w4 = pd.read_csv('data/weather4.csv', index_col=0)
```

```
w1 # Let's look at these Data Frames
```

	Date/Time	Year	Month	Mean Temp (°C)
0	Sep-12	2012	9	15.4
1	Oct-12	2012	10	10.5
2	Nov-12	2012	11	7.2
3	Dec-12	2012	12	4.4
4	Jan-13	2013	1	2.8

```
w2
```

	Date/Time	Year	Month	Mean Temp (°C)
5	Feb-13	2013	2	5.4
6	Mar-13	2013	3	7.2
7	Apr-13	2013	4	9.5
8	May-13	2013	5	13.3
9	Jun-13	2013	6	15.4

```

```

```
w3
```

	Total Rain (mm)	Spd of Max Gust (km/h)
0	5.0	56
1	197.0	74
2	162.8	63
3	183.4	65
4	100.4	39

```
w4
```

	Date/Time	Year	Month	Spd of Max Gust (km/h)
2	Nov-12	2012	11	63
3	Dec-12	2012	12	65
7	Apr-13	2013	4	76
9	Jun-13	2013	6	44

Combining with `pd.concat()`

The simplest way to combine Data Frames in pandas is to use `pd.concat()`, which concatenates them along a shared axis. The default is to concatenate rows:

```

```

```
pd.concat([w1,w2])
```

	Date/Time	Year	Month	Mean Temp (°C)
0	Sep-12	2012	9	15.4
1	Oct-12	2012	10	10.5
2	Nov-12	2012	11	7.2
3	Dec-12	2012	12	4.4
4	Jan-13	2013	1	2.8
5	Feb-13	2013	2	5.4
6	Mar-13	2013	3	7.2
7	Apr-13	2013	4	9.5
8	May-13	2013	5	13.3
9	Jun-13	2013	6	15.4

The above worked well since both Data Frames `w1` and `w2` have the same set of columns. Let's see what happens when we have a few different columns:

```
pd.concat([w1,w4])
```

	Date/Time	Year	Month	Mean Temp (°C)	Spd of Max Gust (km/h)
0	Sep-12	2012	9	15.4	NaN
1	Oct-12	2012	10	10.5	NaN
2	Nov-12	2012	11	7.2	NaN
3	Dec-12	2012	12	4.4	NaN
4	Jan-13	2013	1	2.8	NaN
2	Nov-12	2012	11	NaN	63.0
3	Dec-12	2012	12	NaN	65.0
7	Apr-13	2013	4	NaN	76.0
9	Jun-13	2013	6	NaN	44.0

We get a new frame containing columns from both `w1` and `w4`. The common columns are concatenated, and missing data shows up as `NaN`. Notice that pandas did not know that the indices were 'common', i.e. indices 2 and 3 are repeated in the output.

Next, let's concatenate two Data Frames with shared rows but different columns:

```
pd.concat([w1,w3], axis = 1)
```

	Date/Time	Year	Month	Mean Temp (°C)	Total Rain (mm)	Spd of Max Gust (km/h)
0	Sep-12	2012	9	15.4	5.0	56
1	Oct-12	2012	10	10.5	197.0	74
2	Nov-12	2012	11	7.2	162.8	63
3	Dec-12	2012	12	4.4	183.4	65
4	Jan-13	2013	1	2.8	100.4	39

And again when only some rows are shared:

```
pd.concat([w1,w4], axis = 1)
```

	Date/Time	Year	Month	Mean Temp (°C)	Date/Time	Year	Month	Spd of Max Gust (km/h)
0	Sep-12	2012.0	9.0	15.4	NaN	NaN	NaN	NaN
1	Oct-12	2012.0	10.0	10.5	NaN	NaN	NaN	NaN
2	Nov-12	2012.0	11.0	7.2	Nov-12	2012.0	11.0	63.0
3	Dec-12	2012.0	12.0	4.4	Dec-12	2012.0	12.0	65.0
4	Jan-13	2013.0	1.0	2.8	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN	Apr-13	2013.0	4.0	76.0
9	NaN	NaN	NaN	NaN	Jun-13	2013.0	6.0	44.0

This time pandas knew to use a shared index for rows, but the column indices were treated independently. As a result, we have “duplicate” columns in the output.

We can concatenate as many Data Frames as we want, but each call to `pd.concat` creates a new copy of the data frame. So instead of copying 'one-at-a-time', the best practice is to assemble all required Data Frames into a single list, and only call `pd.concat` once.

```
pd.concat([w1,w2,w3,w4])
```

	Date/Time	Year	Month	Mean Temp (°C)	Total Rain (mm)	Spd of Max Gust (km/h)
0	Sep-12	2012.0	9.0	15.4	NaN	NaN
1	Oct-12	2012.0	10.0	10.5	NaN	NaN
2	Nov-12	2012.0	11.0	7.2	NaN	NaN
3	Dec-12	2012.0	12.0	4.4	NaN	NaN
4	Jan-13	2013.0	1.0	2.8	NaN	NaN
5	Feb-13	2013.0	2.0	5.4	NaN	NaN
6	Mar-13	2013.0	3.0	7.2	NaN	NaN
7	Apr-13	2013.0	4.0	9.5	NaN	NaN
8	May-13	2013.0	5.0	13.3	NaN	NaN
9	Jun-13	2013.0	6.0	15.4	NaN	NaN
0	NaN	NaN	NaN	NaN	5.0	56.0
1	NaN	NaN	NaN	NaN	197.0	74.0
2	NaN	NaN	NaN	NaN	162.8	63.0
3	NaN	NaN	NaN	NaN	183.4	65.0
4	NaN	NaN	NaN	NaN	100.4	39.0
2	Nov-12	2012.0	11.0	NaN	NaN	63.0
3	Dec-12	2012.0	12.0	NaN	NaN	65.0
7	Apr-13	2013.0	4.0	NaN	NaN	76.0
9	Jun-13	2013.0	6.0	NaN	NaN	44.0

We were certainly able to "stick" our data frames together here, but we may not have gained the information we wanted. For example, the data frame above contains entries for both `Mean Temp` and `Total Rain` for November 12, 2012, but these are split across different rows.

If we know beforehand that shared dates should correspond to the same example in our data, it would be good to use this fact when combining the data frames. The next section discuss how to implement this in pandas.

Combining with `pd.Merge`

Another pandas function that is useful for joining Data Frames together is `pd.merge`. This function implements SQL-style joins in pandas. You will learn more about SQL when you study databases in DSCI 513. `pd.merge()`.

When using `pd.concat()`, you have to do all the work beforehand to make sure the rows and/or columns line up just right for the concatenation to give the correct, meaningful result. This can be tricky when working with large Data Frames. With `pd.merge`, we can pass a little more meaningful information to pandas which it uses combine our Data Frames to get the result we intended. Essentially, the matching is done based on columns shared between the Data Frames.

```
pd.merge(w1, w4, how='outer', on = ['Date/Time', 'Month', 'Year'])
```

	Date/Time	Year	Month	Mean Temp (°C)	Spd of Max Gust (km/h)
0	Apr-13	2013	4	NaN	76.0
1	Dec-12	2012	12	4.4	65.0
2	Jan-13	2013	1	2.8	NaN
3	Jun-13	2013	6	NaN	44.0
4	Nov-12	2012	11	7.2	63.0
5	Oct-12	2012	10	10.5	NaN
6	Sep-12	2012	9	15.4	NaN

This time, pandas knew that rows with matching Date/Time, Month and Year should count as the same observation for both frames. But notice that the index was ignored! The resulting Data Frame has an entirely new index, since we were matching on columns. Matching on the index is also possible.

```
pd.merge(w1, w4, how='outer', left_index = True, right_index = True)
```

	Date/Time_x	Year_x	Month_x	Mean Temp (°C)	Date/Time_y	Year_y	Month_y	Spd of Max Gust (km/h)
0	Sep-12	2012.0	9.0	15.4	NaN	NaN	NaN	NaN
1	Oct-12	2012.0	10.0	10.5	NaN	NaN	NaN	NaN
2	Nov-12	2012.0	11.0	7.2	Nov-12	2012.0	11.0	63.0
3	Dec-12	2012.0	12.0	4.4	Dec-12	2012.0	12.0	65.0
4	Jan-13	2013.0	1.0	2.8	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN	Apr-13	2013.0	4.0	76.0
9	NaN	NaN	NaN	NaN	Jun-13	2013.0	6.0	44.0

The `how='outer'` parameter tells pandas to produce a Data Frame containing the full list of keys from both Data Frames. We could restrict this to keys in only one Data Frame:

```
pd.merge(left = w1, right = w4, how='right', on = ['Date/Time', 'Month', 'Year'])
```

	Date/Time	Year	Month	Mean Temp (°C)	Spd of Max Gust (km/h)
0	Nov-12	2012	11	7.2	63
1	Dec-12	2012	12	4.4	65
2	Apr-13	2013	4	NaN	76
3	Jun-13	2013	6	NaN	44

Notice again that the index was not retained when matching on columns.

Let's create a Data Frame of 'seasons' to categorize the different months of the year.

```
seasons = pd.DataFrame({
                    'month':[1,2,3,4,5,6,7,8,9,10,11,12],
                    'season': ['Winter', 'Winter', 'Spring', 'Spring', 'Spring', 'Summer', 'Summer', 'S
                       }
                      )

seasons
```

	month	season
0	1	Winter
1	2	Winter
2	3	Spring
3	4	Spring
4	5	Spring
5	6	Summer
6	7	Summer
7	8	Summer
8	9	Fall
9	10	Fall
10	11	Fall
11	12	Winter

We made this Data Frame “by hand”, using a dictionary object. Dictionaries are another object type in Python, similar to lists but indexed based on “keys” that do not need to be integers. The keys in this case serve as column names when passed to `pd.DataFrame()`.

Now if we have some dataset that includes months as a column, we can merge with `seasons`. For example, we can use the following data set that we saw in Lecture 1 (we are dropping some columns):

```
weather = pd.read_csv('data/YVR_weather_data.csv').dropna(axis=1)
weather.head()
```

	Date/Time	Year	Month	Mean Max Temp (°C)	Mean Min Temp (°C)	Mean Temp (°C)	Extr Max Temp (°C)	Extr Min Temp (°C)
0	Jan-37	1937	1	0.6	-8.1	-3.8	6.1	-16.1
1	Feb-37	1937	2	5.2	-1.3	2.0	10.0	-7.8
2	Mar-37	1937	3	11.7	2.9	7.3	17.2	-1.1
3	Apr-37	1937	4	11.9	4.8	8.4	16.1	1.1
4	May-37	1937	5	16.3	6.6	11.5	20.6	1.7

Let's attempt a left join for `weather` with `seasons`. We will have to tell pandas that `Month` in the left frame matches `month` in the second (note that the strings are not identical).

```
pd.merge(left = weather, right = seasons, how = 'left', left_on = 'Month', right_on = 'month')
```

	Date/Time	Year	Month	Mean Max Temp (°C)	Mean Min Temp (°C)	Mean Temp (°C)	Extr Max Temp (°C)	Extr Min Temp (°C)	month	season
0	Jan-37	1937	1	0.6	-8.1	-3.8	6.1	-16.1	1	Winter
1	Feb-37	1937	2	5.2	-1.3	2.0	10.0	-7.8	2	Winter
2	Mar-37	1937	3	11.7	2.9	7.3	17.2	-1.1	3	Spring
3	Apr-37	1937	4	11.9	4.8	8.4	16.1	1.1	4	Spring
4	May-37	1937	5	16.3	6.6	11.5	20.6	1.7	5	Spring
...	...	...	...	...	...	...	...	...	...	...
912	Feb-13	2013	2	7.8	3.0	5.4	10.4	-1.1	2	Winter
913	Mar-13	2013	3	10.5	3.9	7.2	15.7	-0.7	3	Spring
914	Apr-13	2013	4	12.8	6.2	9.5	17.2	1.0	4	Spring
915	May-13	2013	5	17.1	9.5	13.3	22.2	2.5	5	Spring
916	Jun-13	2013	6	19.3	11.5	15.4	22.0	9.2	6	Summer

917 rows × 10 columns

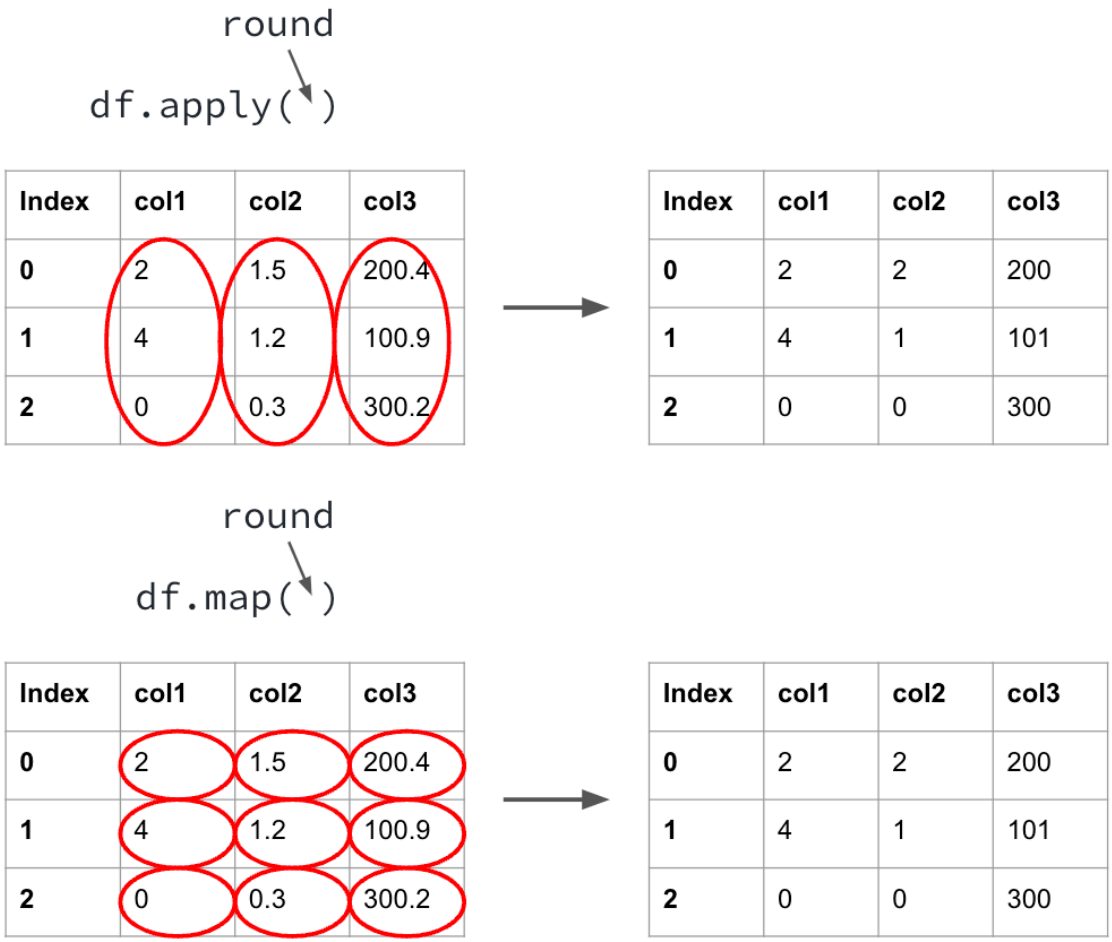
With `pd.merge()`, we can combine data frames in a one-to-one, one-to-many or a many-to-many fashion, leading to a large range of possibilities. You will see many examples of joins in DSCI 513.

Applying Custom Functions

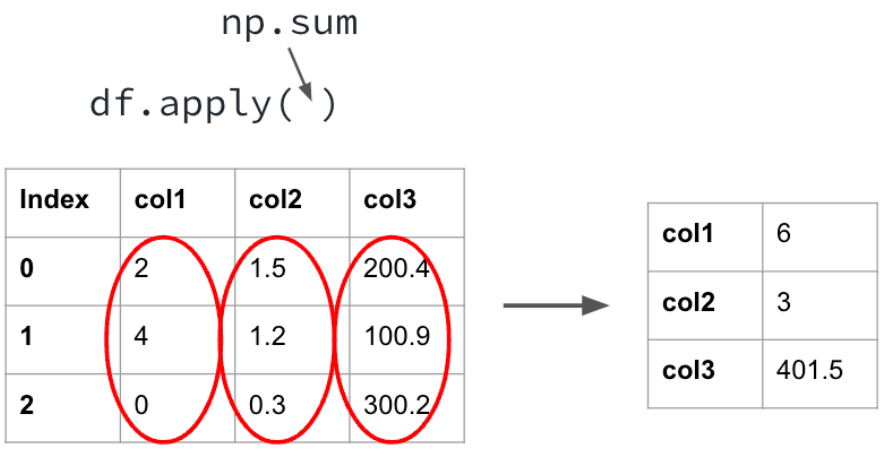
There will be times when you want to apply a function that is not built-in to Pandas. For this, we also have methods:

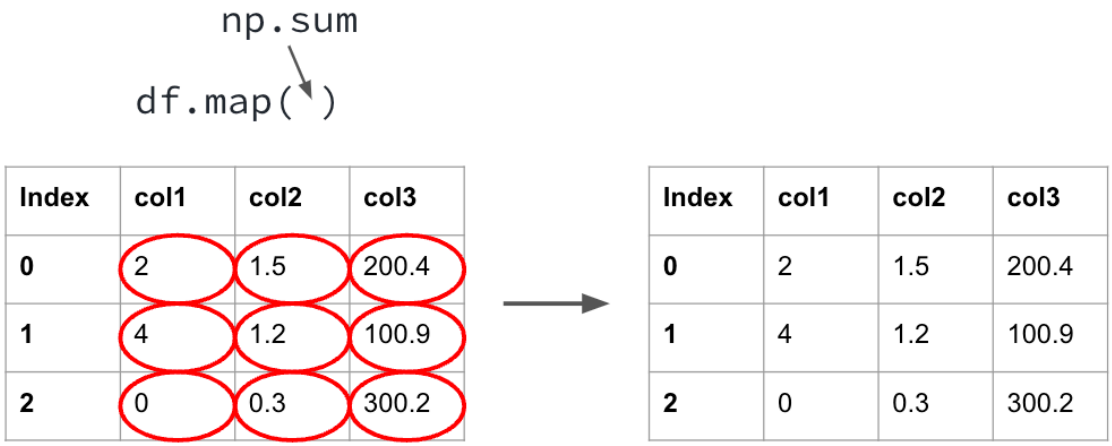
- `df.apply()`, applies a function **column-wise or row-wise** across a dataframe (the function must be able to accept/return an array)
- `df.map()`, applies a function element-wise (so individually) across **every element** in the data frame (meant for functions that accept/return single values at a time)
- `series.apply()`, same as above for Pandas `Series`.
- `series.map()`, also for Series, but optionally accepts a dictionary as input.

It is important to understand how `.apply()` and `.map()` differ. Sometimes it appears as though these functions work the same. This is the case for functions which accept and return single values at a time, like the `round` function:



However, when using `.apply()` and `.map()` with methods/functions that act on a series or array and return a single value, like `np.sum`, the objects they return are quite different:





It is also important to know how `pandas.DataFrame.apply()` works with regards to what `axis=0` and `axis=1` means. This clarification is important because in many other pandas functions/methods, `axis=0` means row-wise, and `axis=1` means column-wise. But that is not the case here. From the **`pandas.DataFrame.apply()`** docs:

"Objects passed to the function are Series objects whose index is either the DataFrame's index (axis=0) or the DataFrame's columns (axis=1)."

So for `pandas.DataFrame.apply()`:

- `axis=0` means the **columns** (saying you want the index to be the DataFrame's index)

- `axis=1` means the **rows** (saying you want the index to be the DataFrame's columns)

For `pandas.DataFrame.apply()` `axis=0` is the default, meaning it works column-wise unless you specify otherwise (as shown in the examples above).

Here's some examples of using `.apply()` and `.map()` with our weather data:

```
weather[['Month', 'Mean Temp (°C)']].apply(np.log) # we will see more from numpy in future lectures
```

	Month	Mean Temp (°C)
0	0.000000	NaN
1	0.693147	0.693147
2	1.098612	1.987874
3	1.386294	2.128232
4	1.609438	2.442347
...	...	...
912	0.693147	1.686399
913	1.098612	1.974081
914	1.386294	2.251292
915	1.609438	2.587764
916	1.791759	2.734368

917 rows × 2 columns

```
weather['Mean Temp (°C)'].apply(int) # apply is a method for both Data Frames and Series
```

```
0      -3
1       2
2       7
3       8
4      11
       ..
912     5
913     7
914     9
915    13
916    15
Name: Mean Temp (°C), Length: 917, dtype: int64
```

We provide a dictionary as input to `Series.map`.

```
weather[['Month', 'Mean Temp (°C)']].apply(np.sum)
```

```
Month             5940.0
Mean Temp (°C)    9198.1
dtype: float64
```

```
seasons['season'].map(
                      {'Winter':'Cold', 'Spring':'Not Cold', 'Summer': 'Warm'}
                    )
```

```
0         Cold
1         Cold
2     Not Cold
3     Not Cold
4     Not Cold
5         Warm
6         Warm
7         Warm
8          NaN
9          NaN
10         NaN
11        Cold
Name: season, dtype: object
```

Note that `'Fall'` did not appear as a key in the dictionary supplied, and the output shows `NaN` for the corresponding entries.

Grouping

Often we are interested in examining specific groups in our data. In pandas, `df.groupby()` allows us to group our data based on one or more variables. It is analgous to the `group_by` function in R

```
imdb = pd.read_csv('data/imdb.csv')
imdb.head()
```

	Series_Title	Released_Year	Certificate	Runtime	Genre	IMDB_Rating	Meta_score	Director	S
0	The Shawshank Redemption	1994	A	142 min	Drama	9.3	80.0	Frank Darabont	Rob
1	The Godfather	1972	A	175 min	Crime, Drama	9.2	100.0	Francis Ford Coppola	Ma Bra
2	The Dark Knight	2008	UA	152 min	Action, Crime, Drama	9.0	84.0	Christopher Nolan	Chri
3	The Godfather: Part II	1974	A	202 min	Crime, Drama	9.0	90.0	Francis Ford Coppola	Pa
4	12 Angry Men	1957	U	96 min	Crime, Drama	9.0	96.0	Sidney Lumet	H Fo

Let's group this Data Frame on `Released_Year`:

```
imdb.groupby(by = 'Released_Year')
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x15c4253d0>
```

What is a `DataFrameGroupBy` object? It's really just a dictionary of index-mappings! The keys represent the different groups, and each key is mapped to a list of indices corresponding to that group. We can look at them directly if we really wanted to:

```
imdb.groupby(by = 'Released_Year').groups
```

```
{1920: [321], 1921: [127], 1922: [568], 1924: [194], 1925: [193, 462], 1926: [320], 1927: [126, 319], 1
```

We can access a specific group using the `get_group()` method.

```
imdb.groupby(by='Released_Year').get_group(1995)
```

	Series_Title	Released_Year	Certificate	Runtime	Genre	IMDB_Rating	Meta_score	Director
27	Se7en	1995	A	127 min	Crime, Drama, Mystery	8.6	65.0	David Fincher
41	The Usual Suspects	1995	A	106 min	Crime, Mystery, Thriller	8.5	77.0	Bryan Singer
101	Toy Story	1995	U	81 min	Animation, Adventure, Comedy	8.3	95.0	John Lasseter
102	Braveheart	1995	A	178 min	Biography, Drama, History	8.3	68.0	Mel Gibson
164	Heat	1995	A	170 min	Crime, Drama, Thriller	8.2	76.0	Michael Mann
165	Casino	1995	A	178 min	Crime, Drama	8.2	73.0	Martin Scorsese
256	Underground	1995	NaN	170 min	Comedy, Drama, War	8.1	NaN	Emir Kusturica
257	La haine	1995	UA	98 min	Crime, Drama	8.1	NaN	Mathieu Kassovitz
258	Dilwale Dulhania Le Jayenge	1995	U	189 min	Drama, Romance	8.1	NaN	Aditya Chopra
259	Before Sunrise	1995	R	101 min	Drama, Romance	8.1	77.0	Richard Linklater

	Series_Title	Released_Year	Certificate	Runtime	Genre	IMDB_Rating	Meta_score	Director
393	Twelve Monkeys	1995	A	129 min	Mystery, Sci-Fi, Thriller	8.0	74.0	Terry Gilliam
394	Kôkaku Kidôtai	1995	UA	83 min	Animation, Action, Crime	8.0	76.0	Mamoru Oshii
518	Mimi wo sumaseba	1995	U	111 min	Animation, Drama, Family	7.9	75.0	Yoshifumi Kondô
813	A Little Princess	1995	U	97 min	Drama, Family, Fantasy	7.7	83.0	Alfonso Cuarón
814	Do lok tin si	1995	UA	99 min	Comedy, Crime, Drama	7.7	71.0	Kar-Wai Wong
962	Sense and Sensibility	1995	U	136 min	Drama, Romance	7.6	84.0	Ang Lee
963	Die Hard: With a Vengeance	1995	A	128 min	Action, Adventure, Thriller	7.6	58.0	John McTiernan
964	Dead Man	1995	R	121 min	Adventure, Drama, Fantasy	7.6	62.0	Jim Jarmusch
965	Apollo 13	1995	U	140 min	Adventure, Drama, History	7.6	77.0	Ron Howard
966	The Bridges of Madison County	1995	A	135 min	Drama, Romance	7.6	69.0	Clint Eastwood

The usual thing to do, however, is to apply aggregation functions to the `groupby` object. For example, we could take the mean of the numeric columns. Use `numeric_only=True` to tell pandas to ignore non-numeric columns.

```
imdb.groupby(by='Released_Year').mean(numeric_only=True)
```

Released_Year	IMDB_Rating	Meta_score	No_of_Votes	Gross
1920	8.100000	NaN	5.742800e+04	NaN
1921	8.300000	NaN	1.133140e+05	5450000.0
1922	7.900000	NaN	8.879400e+04	NaN
1924	8.200000	NaN	4.198500e+04	977375.0
1925	8.100000	97.000000	7.705350e+04	2750485.0
...	...	...	...	...
2017	7.890909	79.473684	2.586361e+05	103065642.6
2018	7.994737	77.692308	2.195192e+05	186268383.0
2019	7.995652	76.904762	2.601555e+05	150421418.0
2020	8.133333	82.750000	8.412700e+04	NaN
3010	8.800000	74.000000	2.067042e+06	292576195.0

100 rows × 4 columns

Even better would be to select the numeric columns ahead of time, and then call `grouby()` and `mean()`. We can apply multiple functions using `aggregate()`.

```
(
    imdb
    .loc[:, ['Released_Year', 'IMDB_Rating', 'Meta_score', 'No_of_Votes']]
    .groupby(by='Released_Year')
    .aggregate(['mean', 'sum', 'count'])
)
```

	IMDB_Rating			Meta_score			No_of_Votes		
	mean	sum	count	mean	sum	count	mean	sum	count
Released_Year									
1920	8.100000	8.1	1	NaN	0.0	0	5.742800e+04	57428	1
1921	8.300000	8.3	1	NaN	0.0	0	1.133140e+05	113314	1
1922	7.900000	7.9	1	NaN	0.0	0	8.879400e+04	88794	1
1924	8.200000	8.2	1	NaN	0.0	0	4.198500e+04	41985	1
1925	8.100000	16.2	2	97.000000	97.0	1	7.705350e+04	154107	2
...	...	...	...	...	...	...	...	...	...
2017	7.890909	173.6	22	79.473684	1510.0	19	2.586361e+05	5689995	22
2018	7.994737	151.9	19	77.692308	1010.0	13	2.195192e+05	4170864	19
2019	7.995652	183.9	23	76.904762	1615.0	21	2.601555e+05	5983576	23
2020	8.133333	48.8	6	82.750000	331.0	4	8.412700e+04	504762	6
3010	8.800000	8.8	1	74.000000	74.0	1	2.067042e+06	2067042	1

100 rows × 9 columns

We could also apply different functions to different columns.

```
imdb.groupby(by="Released_Year").agg(
    {
        "Meta_score": ["max", "min", "mean"],
        "Gross": ["sum"]
    }
)
```

	Meta_score			Gross
	max	min	mean	sum
Released_Year				
1920	NaN	NaN	NaN	0.000000e+00
1921	NaN	NaN	NaN	5.450000e+06
1922	NaN	NaN	NaN	0.000000e+00
1924	NaN	NaN	NaN	9.773750e+05
1925	97.0	97.0	97.000000	5.500970e+06
...	...	...	...	...
2017	94.0	60.0	79.473684	2.061313e+09
2018	96.0	49.0	77.692308	2.607757e+09
2019	96.0	51.0	76.904762	2.406743e+09
2020	90.0	77.0	82.750000	0.000000e+00
3010	74.0	74.0	74.000000	2.925762e+08

100 rows × 4 columns

Later on, we will learn how to write our own Python functions. Such 'custom' functions can also be passed to `aggregate()`.

Note that we can pass multiple columns to `groupby()`. The groups will be indexed based on all combinations of entries that appear in the listed columns

```
imdb.groupby(by=["Released_Year", "Certificate"]).agg(
    {
        "Meta_score": ["mean"],
        "Gross": ["sum"]
    }
)
```

		Meta_score	Gross
		mean	sum
Released_Year	Certificate		
1921	Passed	NaN	5450000.0
1924	Passed	NaN	977375.0
1925	Passed	NaN	5450000.0
1926	Passed	NaN	1033895.0
1927	Passed	NaN	539540.0
...	...	...	...
2020	PG-13	90.0	0.0
	R	77.0	0.0
	U	83.0	0.0
	UA	NaN	0.0
3010	UA	74.0	292576195.0

330 rows × 2 columns

Finally, you can `aggregate()` on a non-grouped data frame as well. This is essentially what `DataFrame.describe()` does under the hood.

```
(
    imdb
    .loc[:, ['IMDB_Rating', 'Meta_score', 'No_of_Votes']]
    .agg(['mean', 'min', 'count'])
)
```

	IMDB_Rating	Meta_score	No_of_Votes
mean	7.9493	77.97153	273692.911
min	7.6000	28.00000	25088.000
count	1000.0000	843.00000	1000.000