Data Wrangling: Join, Combine, and Reshape

Prof. Gheith Abandah

Reference

- **Chapter 8**
- Wes McKinney, **Python for Data Analysis**: Data Wrangling with Pandas, NumPy, and IPython, O'Reilly Media, 2nd Edition, 2018.
  - Material: https://github.com/wesm/pypop-book

Data Wrangling: Join, Combine, and Reshape

- **Data wrangling** is the process of gathering, selecting, and transforming data to answer an analytical question.
- In many applications, **data** may be **spread** across a number of files or databases or be arranged in a **form** that is **not easy to analyze**.
- This topic focuses on **tools** to help **combine**, **join**, and **rearrange** data.

Outline

8.1 Hierarchical Indexing

8.2 Combining and Merging Datasets

8.3 Reshaping and Pivoting

Outline

8.1 Hierarchical Indexing

8.2 Combining and Merging Datasets

8.3 Reshaping and Pivoting

- Introduction
- Reordering and Sorting Levels
- Summary Statistics by Level
- Indexing with a DataFrame's columns

8.1 Hierarchical Indexing

- **Hierarchical indexing** is having multiple index levels on an axis.
- Allows you to **work with higher dimensional data** in a lower dimensional form.
- **Example**: Tracking population (millions) using pandas **Series**.

```
pop = pd.Series([34, 37, 19, 20,
                 21, 25],
      index=[['CA', 'CA', 'NY',
              'NY', 'TX', 'TX'],
             [2000, 2010, 2000,
              2010, 2000, 2010]])
```

```
CA  2000    34
    2010    37
NY  2000    19
    2010    19
TX  2000    21
    2010    25
```

8.1 Hierarchical Indexing

- Try accessing:
  - **Index**
  - **Elements**
  - **Slices**

```
pop.index
pop['CA', 2000]
pop['CA']
pop['NY':'TX']
pop.loc[['CA', 'TX']]
pop.loc[:, 2010]
```

- Try `unstack` and `stack`.

```
pop.unstack()
pop.unstack().stack()
```

8.1 Hierarchical Indexing

- With a **DataFrame**, **both axis** can have a **hierarchical index**.

```
popf = pd.DataFrame(
    [[34, 18, 16], [37, 19, 16],
     [19, 10, 9], [20, 10, 10],
     [21, 11, 10], [25, 13, 12]],
    index=[['CA', 'CA', 'NY',
            'NY', 'TX', 'TX'],
           [2000, 2010, 2000,
            2010, 2000, 2010]],
    columns=[['Pop', 'Pop', 'Pop'],
             ['Total', 'Male', 'Female']])
```

		Pop		
		Total	Male	Female
CA	2000	34	18	16
	2010	37	19	16
NY	2000	19	10	9
	2010	20	10	10
TX	2000	21	11	10
	2010	25	13	12

8.1 Hierarchical Indexing

- The **hierarchical levels** can have **names** (as strings or any Python objects).

- **Try**:
- `popf['Pop']`
- `popf['Pop', 'Total']['CA']`
- `popf['Pop', 'Total']['CA', 2000]`
- `popf.loc['CA', 2000]`

```
popf.index.names = ['State', 'Year']
popf.columns.names = ['Key', 'Details']
```

Key		Pop		
Details		Total	Male	Female
State	Year			
CA	2000	34	18	16
	2010	37	19	16
NY	2000	19	10	9
	2010	20	10	10
TX	2000	21	11	10
	2010	25	13	12

Reordering and Sorting Levels

- You can **rearrange** the **order** of the **levels** on an axis.
- The **`swaplevel`** takes two level numbers or names and returns a new object with the levels interchanged.

```
popf.swaplevel('State', 'Year')
```

Key		Pop		
Details		Total	Male	Female
Year	State			
2000	CA	34	18	16
2010	CA	37	19	16
2000	NY	19	10	9
2010	NY	20	10	10
2000	TX	21	11	10
2010	TX	25	13	12

Reordering and Sorting Levels

- You can **sort** the data by the values in one **specific level**.
- **`sort_index`** sorts the data using only the values in a single level.
- Sorting provides better **performance**.

```
popf.swaplevel(
      0, 1).sort_index(level=0)
```

Key		Pop		
Details		Total	Male	Female
Year	State			
2000	CA	34	18	16
	NY	19	10	9
	TX	21	11	10
2010	CA	37	19	16
	NY	20	10	10
	TX	25	13	12

Summary Statistics by Level

- Many descriptive and summary statistics have a **level option** in which you can specify the level you want **to aggregate** by on a particular axis.

```
popf.min(level='State')
Key        Pop
Details Total Male Female
State
CA         34   18     16
NY         19   10      9
TX         21   11     10

popf.min(level='Key', axis=1)
Key           Pop
State Year
CA    2000     16
      2010     16
NY    2000      9
      2010     10
TX    2000     10
      2010     12
```

Indexing with a DataFrame's columns

- You can convert some DataFrame columns to index by **set_index**.

```
before
   a  b    c  d
0  0  7  one  0
1  1  6  one  1
2  2  5  one  2
3  3  4  two  0
4  4  3  two  1
5  5  2  two  2
6  6  1  two  3
```

```
after
         a  b
c   d
one 0    0  7
    1    1  6
    2    2  5
two 0    3  4
    1    4  3
    2    5  2
    3    6  1
```

```
frame2 = frame.set_index(
                    ['c', 'd'])
```

The opposite function is:
`frame2.reset_index()`

Outline

8.1 Hierarchical Indexing

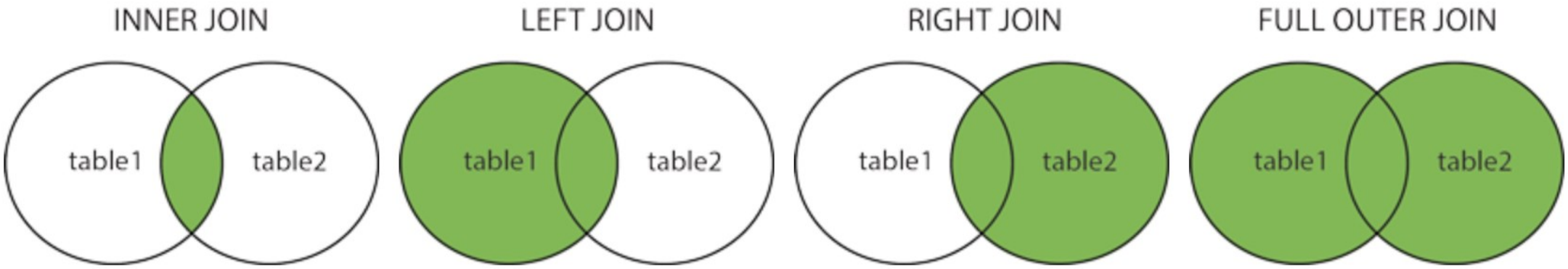
8.2 Combining and Merging Datasets

8.3 Reshaping and Pivoting

- Database-Style DataFrame Joins
- Merging on Index
- Concatenating Along an Axis
- Combining Data with Overlap

Database-Style DataFrame Joins

- **Join** operations are **central** to **relational databases** (e.g., SQL-based).
- **Reference**: https://www.w3schools.com/sql/sql_join.asp



Database-Style DataFrame Joins

- **Merge** or join operations **combine datasets** by linking rows using one or more keys.
- The **merge** function in pandas is the main entry point for using join algorithms on your data.
- **Many to one inner join** example:

```
df1
   data1 key
0      0   b
1      1   b
2      2   a
3      3   c
4      4   a
```

```
df2
   data2 key
0      0   a
1      1   b
2      2   d
```

```
pd.merge(df1, df2)
  key  data1  data2
0   b      0      1
1   b      1      1
2   a      2      0
3   a      4      0
```

Same result with:

```
pd.merge(df1, df2,
     on='key')
```

Database-Style DataFrame Joins

- If the **column names** are **different** in each object, you can **specify them** separately.

```
df3 = pd.DataFrame({'lkey': ['b',
    'c', 'a'], 'data1': range(3)})
df4 = pd.DataFrame({'rkey': ['a',
    'b', 'd'], 'data2': range(3)})
pd.merge(df3, df4, left_on='lkey',
         right_on='rkey')
  lkey  data1 rkey  data2
0    b      0    b      1
1    a      2    a      0
```

Database-Style DataFrame Joins

- In addition to the default `'inner'` join, you can specify:
  - `'left'`
  - `'right'`
  - `'outer'`

```
pd.merge(df3, df4, left_on='lkey',
         right_on='rkey',
         how='outer')
```

	lkey	data1	rkey	data2
0	b	0.0	b	1.0
1	c	1.0	NaN	NaN
2	a	2.0	a	0.0
3	NaN	NaN	d	2.0

Database-Style DataFrame Joins

- **Many-to-many** joins form the **Cartesian product** of the rows.

```
df1 = pd.DataFrame({'key': ['b',
          'b', 'a', 'c'],
          'data1': range(4)})
df2 = pd.DataFrame({'key': ['a',
          'b', 'a', 'd'],
          'data2': range(4)})
pd.merge(df1, df2, how='left')
  key  data1  data2
0   b      0    1.0
1   b      1    1.0
2   a      2    0.0
3   a      2    2.0
4   c      3    NaN
```

Database-Style DataFrame Joins

- To merge with **multiple keys**, pass a list of column names.

```
left = pd.DataFrame(
  {'key1': ['foo', 'foo', 'bar'],
   'key2': ['one', 'two', 'one'],
   'lval': [1, 2, 3]})
right = pd.DataFrame(
  {'key1': ['foo','foo','bar','bar'],
   'key2': ['one','one','one','two'],
   'rval': [4, 5, 6, 7]})
pd.merge(left, right,
     on=['key1', 'key2'], how='outer')
```

	key1	key2	lval	rval
0	foo	one	1.0	4.0
1	foo	one	1.0	5.0
2	foo	two	2.0	NaN
3	bar	one	3.0	6.0
4	bar	two	NaN	7.0

Database-Style DataFrame Joins

- Pandas has default treatment of **overlapping column names**.
- You can also use the **`suffixes`** option for specifying strings to append to overlapping names in the left and right DataFrame objects.

```
pd.merge(left, right, on='key1')
  key1 key2_x  lval key2_y  rval
0  foo    one     1    one     4
…

pd.merge(left, right, on='key1',
         suffixes=('_left', '_right'))
  key1 key2_left  lval key2_right  rval
0  foo       one     1         one     4
…
```

Merge function arguments

Argument	Description
`left`	DataFrame to be merged on the left side.
`right`	DataFrame to be merged on the right side.
`how`	One of `'inner'`, `'outer'`, `'left'`, or `'right'`; defaults to `'inner'`.
`on`	Column names to join on. Must be found in both DataFrame objects. If not specified and no other join keys given, will use the intersection of the column names in `left` and `right` as the join keys.
`left_on`	Columns in `left` DataFrame to use as join keys.
`right_on`	Analogous to `left_on` for `left` DataFrame.
`left_index`	Use row index in `left` as its join key (or keys, if a MultiIndex).
`right_index`	Analogous to `left_index`.
`sort`	Sort merged data lexicographically by join keys; `True` by default (disable to get better performance in some cases on large datasets).
`suffixes`	Tuple of string values to append to column names in case of overlap; defaults to `('_x', '_y')` (e.g., if `'data'` in both DataFrame objects, would appear as `'data_x'` and `'data_y'` in result).
`copy`	If `False`, avoid copying data into resulting data structure in some exceptional cases; by default always copies.
`indicator`	Adds a special column `_merge` that indicates the source of each row; values will be `'left_only'`, `'right_only'`, or `'both'` based on the origin of the joined data in each row.

Merging on Index

- The **merge key(s)** can be **in the index**.
- You can pass **`left_index=True`** or **`right_index=True`** (or both).

left

	key1	key2	data
0	Ohio	2000	0.0
1	Ohio	2001	1.0
2	Ohio	2002	2.0
3	Nevada	2001	3.0
4	Nevada	2002	4.0

right

		event1	event2
Nevada	2001	0	1
	2000	2	3
Ohio	2000	4	5
	2000	6	7
	2001	8	9
	2002	10	11

```
pd.merge(left, right,
         left_on=['key1', 'key2'],
         right_index=True)
```

	key1	key2	data	event1	event2
0	Ohio	2000	0.0	4	5
0	Ohio	2000	0.0	6	7
1	Ohio	2001	1.0	8	9
2	Ohio	2002	2.0	10	11
3	Nevada	2001	3.0	0	1

Merging on Index

- When **indices are similar**, you can also use the **join** method.

- You can also join **multiple** DataFrames at once.

```
left2
   Ohio  Nevada
a   1.0     2.0
c   3.0     4.0
e   5.0     6.0
```

```
right2
   Missouri  Alabama
b       7.0      8.0
c       9.0     10.0
d      11.0     12.0
e      13.0     14.0
```

```
left2.join(right2, how='outer')
```

```
   Ohio  Nevada  Missouri  Alabama
a   1.0     2.0       NaN      NaN
b   NaN     NaN       7.0      8.0
c   3.0     4.0       9.0     10.0
d   NaN     NaN      11.0     12.0
e   5.0     6.0      13.0     14.0
```

```
left2.join([right2, right3])
```

Concatenating Along an Axis

- **Concatenation**, **binding**, or **stacking** is supported by `concat` function.
- You can **glue** multiple **Series**.
- You can use keys to **identify** the **origin** of each entry.

```
s1
a    0
b    1
```

```
s2
c    2
d    3
e    4
```

```
s3
f    5
g    6
```

```
s1 = pd.Series([0, 1], index=['a', 'b'])
s2 = pd.Series([2, 3, 4],
               index=['c', 'd', 'e'])
s3 = pd.Series([5, 6], index=['f', 'g'])
pd.concat([s1, s2, s3])
pd.concat([s1, s2, s3],
          keys=['one', 'two', 'three'])
```

```
one    a    0
       b    1
two    a    0
       b    1
three  f    5
       g    6
```

Concatenating Along an Axis

- **concat** also work on **DataFrames**.

```
df1
   one  two
a    0    1
b    2    3
c    4    5
```

```
df2
   three  four
a      5     6
c      7     8
```

```
pd.concat([df1, df2], axis=1,
          keys=['level1', 'level2'])
```

```
  level1      level2
     one two   three four
a      0   1     5.0  6.0
b      2   3     NaN  NaN
c      4   5     7.0  8.0
```

- When the row index has **no relevant data**, pass **ignore_index=True**.

```
pd.concat([df1, df2], ignore_index=True)
```

Stacking

Combining Data with Overlap

- When you want to **concatenate** two objects and **patching** the **NA** values from the caller object, use **combine_first**.

```
df1.combine_first(df2)
```

df1

	a	b	c
0	1.0	NaN	2
1	NaN	2.0	6
2	5.0	NaN	10
3	NaN	6.0	14

df2

	a	b
0	5.0	NaN
1	4.0	3.0
2	NaN	4.0
3	3.0	6.0
4	7.0	8.0

	a	b	c
0	1.0	NaN	2.0
1	4.0	2.0	6.0
2	5.0	4.0	10.0
3	3.0	6.0	14.0
4	7.0	8.0	NaN

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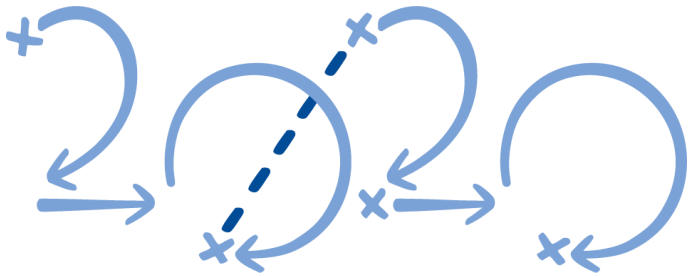

- Reshaping with Hierarchical Indexing
- Pivoting “Long” to “Wide” Format
- Pivoting “Wide” to “Long” Format

Reshaping with Hierarchical Indexing

- Pandas objects can be reshaped using:
  - `T` (returns a transposed view)
  - `stack`: "rotates" or pivots from the columns in the data to the rows.
  - `unstack`: pivots from the rows into the columns.
- **Example**: Find the totals over all states.

Key		Pop		
Details		Total	Male	Female
State	Year			
CA	2000	34	18	16
	2010	37	19	16
NY	2000	19	10	9
	2010	20	10	10
TX	2000	21	11	10
	2010	25	13	12

```
popf.unstack().sum()
```

Reshaping with Hierarchical Indexing

- By default the **innermost** level is (un)stacked.
- When you unstack, the level unstacked becomes the innermost.
- You can (un)stack a different level by passing a level **number** or **name**.
- Unstacking might introduce **missing data**.

```
popf.unstack()
```

Key	Pop					
Details	Total		Male		Female	
Year	2000	2010	2000	2010	2000	2010
State						
CA	34	37	18	19	16	16
NY	19	20	10	10	9	10
TX	21	25	11	13	10	12

```
popf.unstack(0)
popf.unstack('State')
```

Pivoting *Long* to *Wide* Format

- When you want to unstack based on keys (not index), use **pivot**.

```
pivot(index,
      columns,
      values)
```

```
data
    Name     Item  Value
0   Mohd      Age  22.00
1   Mohd   Height   1.75
2   Mohd   Weight  75.00
3   Tala      Age  21.00
4   Tala   Height   1.65
5   Tala   Weight  62.00

data.pivot('Name', 'Item', 'Value')
Item   Age  Height  Weight
Name
Mohd  22.0    1.75    75.0
Tala  21.0    1.65    62.0
```

Pivoting *Wide* to *Long* Format

- When you want to stack based on keys (not index), use **melt**.

```
pd.melt(df,
        id_vars,
        value_vars)
```

```
data
 Dept   Exps   Sales   Serves
0    A   1200    3000      500
1    B   2300     400     2500
```

```
pd.melt(data, id_vars=['Dept'],
    value_vars=['Sales', 'Serves'])
  Dept variable  value
0    A    Sales   3000
1    B    Sales    400
2    A   Serves    500
3    B   Serves   2500
```

Summary

8.1 Hierarchical Indexing

8.2 Combining and Merging Datasets

8.3 Reshaping and Pivoting