Pandas

- Jake VanderPlas. 2016. *Python Data Science Handbook: Essential Tools for Working with Data*. O'Reilly Media, Inc.
- Chapter 3 - Data Manipulation with Pandas
- https://github.com/jakevdp/PythonDataScienceHandbook

Pandas provides:

- Rich I/O Capabilities (read/write data from/to CSV, Excel, SQL, JSON, etc.)
- 1-dimensional (**Series**) and 2-dimensional tabular (**DataFrame**) data structures.
- Data flexibility (handles missing data, time series, and heterogeneous data types).
- Labeled Rows and columns for data alignment
- Flexible indexing, slicing, fancy indexing, and subsetting of large datasets.

In [1]:
```
import numpy as np
import pandas as pd

pd.__version__
```

Out[1]:
```
'2.2.3'
```

In [2]:
```
# type TAB to get the numpy namespace
#pd.
```

In [3]:
```
def pprint(*args, sep='\n', end='\n', userepr=True, align=False, breakline=False, indent='
    "Evaluate and pretty print"
    if align :
        max_arg_len = max(map(len,args))
        txt2txt = lambda txt : ' '*(max_arg_len-len(txt)) + txt
        args = list(map(txt2txt, args))
    geval = lambda txt : eval(txt, globals())
    txt2txt = lambda txt : f'{repr(geval(txt))}' if userepr else f'{geval(txt)}'
    output = map(txt2txt, args)
    txt2txt = lambda txt : f'{txt} = '
    prefix = map(txt2txt, args)
    if breakline :
        po2txt = lambda p,o : (p+'\n'+o).replace('\n','\n'+indent)
    else:
        po2txt = lambda p,o : (p+o).replace('\n','\n'+' '*len(p))
    print(*map(po2txt, prefix, output), sep=sep, end=end)

class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier, monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
        return '\n'.join(self.template.format(a, eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

```
from IPython.display import HTML
HTML("""
<style>
.dataframe {
    font-size: 80% !important; /* Adjust the percentage as needed */
}
</style>
""")
```

Out[3]:

Pandas Series

- One-dimensional array of indexed data
- Two key attributes:
  - `values` : NumPy array
  - `index` : an array-like object of type `pd.Index`

In [4]:
```
d = pd.Series([0.25, 0.5, 0.75, 1.0])
pprint('d', 'd.values', 'd.index', align=True)
```

```
       d = 0    0.25
           1    0.50
           2    0.75
           3    1.00
           dtype: float64
d.values = array([0.25, 0.5 , 0.75, 1.  ])
 d.index = RangeIndex(start=0, stop=4, step=1)
```

In [5]:
```
d = pd.Series([0.25, 0.5, 0.75, 1.0])
pprint('d', 'd.values', 'd.index', align=True)
```

```
       d = 0    0.25
           1    0.50
           2    0.75
           3    1.00
           dtype: float64
d.values = array([0.25, 0.5 , 0.75, 1.  ])
 d.index = RangeIndex(start=0, stop=4, step=1)
```

Series can be created from NumPy arrays:

In [6]:
```
d = pd.Series(np.linspace(0,4,6))
d
```

Out[6]:
```
0    0.0
1    0.8
2    1.6
3    2.4
4    3.2
5    4.0
dtype: float64
```

A series can be indexed just like a NumPy array:

In [7]:
```
d = pd.Series(np.arange(10,15))
pprint('d[3]')  # simple index --> scalar
pprint('d[3:]', 'd[3:4]')  # slice --> series
pprint('d[[1,3,0]]', 'd[[1]]')  # fancy index --> series
```

```
d[3] = 13
d[3:] = 3    13
        4    14
        dtype: int64
d[3:4] = 3    13
         dtype: int64
d[[1,3,0]] = 1    11
             3    13
             0    10
             dtype: int64
d[[1]] = 1    11
         dtype: int64
```

But... Pandas Series can have an **explicit index**

- If not provided, an **implicit int index** is used `[0,1,...,n-1]`

In [8]:
```python
d = pd.Series(np.arange(10,15), index=["a","b","c","d","e"])
pprint('d')
# WARNING "treating keys as positions is deprecated"  --> use Series.iloc[pos]
#pprint('d[1]')
pprint('d["b"]')
```

```
d = a    10
    b    11
    c    12
    d    13
    e    14
    dtype: int64
d["b"] = 11
```

Slicing - Case 1 - non-integer explicit index

- Both non-integer (explicit) and integer (implicit) slices can be used.
- non-integer slice → **label-based indexing** → $[from, to]$
- integer slice → **position-based indexing** → $[from, to)$

In [9]:
```python
d = pd.Series([100,101,102,103,104], index=["a","b","c","d","e"])
pprint('d')
pprint('d["a"]', 'd["c"]', 'd["a":"c"].values')   # explicit index
pprint('d[0:2].values')                           # implicit index
```

```
d = a    100
    b    101
    c    102
    d    103
    e    104
    dtype: int64
d["a"] = 100
d["c"] = 102
d["a":"c"].values = array([100, 101, 102])
d[0:2].values = array([100, 101])
```

Slicing - Case 2 - integer explicit index

- Slicing is always referred to implicit indexes.
- integer slice → **position-based indexing** → $[from, to)$

In [10]:
```
d = pd.Series([100,101,102,103,104], index=[1,5,4,2,3])
pprint('d')
pprint('d[1]', 'd[3]')  # explicit index
pprint('d[1:3].values') # implicit index
```

```
d = 1    100
    5    101
    4    102
    2    103
    3    104
    dtype: int64
d[1] = 100
d[3] = 104
d[1:3].values = array([101, 102])
```

Fancy Indexing

- Label-based indexing
- Using position-based indexing is deprecated

In [11]:
```
d = pd.Series([100,101,102,103,104], index=["a","b","c","d","e"])
pprint('d[["a","b","c"]].values')   # implicit index
# WARNING "treating keys as positions is deprecated"  --> use Series.iloc[pos]
#pprint('d[[1,2,3]].values')   # implicit index

d = pd.Series([100,101,102,103,104], index=[1,5,4,2,3])
pprint('d[[1,2,3]].values')   # explicit index
```

```
d[["a","b","c"]].values = array([100, 101, 102])
d[[1,2,3]].values = array([100, 103, 104])
```

Series and dictionaries

- Series are kind of specialized Python dictionaries $\{index_{typed\ \&\ ordered} \rightarrow value_{typed}\}$
- `pd.Series(dict)` → create a Series from a dictionary
- `pd.Series.to_dict()` → create a dictionary from a Series

In [12]:
```
d1 = pd.Series([100,101,102], index=["a","b","c"])
x = d1.to_dict()
d2 = pd.Series(x)
pprint('d1','x','d2')
```

```
d1 = a    100
     b    101
     c    102
     dtype: int64
x = {'a': 100, 'b': 101, 'c': 102}
d2 = a    100
     b    101
     c    102
     dtype: int64
```

- `.keys()` → `.index`

In [13]:
```
d = pd.Series([100,101,102,103,104], index=["a","b","c","d","e"])
pprint('type(d.index) == type(d.keys())')
```

```
pprint('d.index == d.keys()')
pprint('d.index is d.keys()')
```

```
type(d.index) == type(d.keys()) = True
d.index == d.keys() = array([ True,  True,  True,  True,  True])
d.index is d.keys() = True
```

- $\nexists$ `.values()`

In [14]:
```
d.values
# TypeError: 'numpy.ndarray' object is not callable
#d.values()
```

Out[14]:
```
array([100, 101, 102, 103, 104])
```

- `.items()` → `zip` object of `(index,value)`

In [15]:
```
d = pd.Series([100,101,102,103,104], index=["a","b","c","d","e"])
pprint('d.items()')
print(*d.items())
```

```
d.items() = <zip object at 0x7f91e8418dc0>
('a', 100) ('b', 101) ('c', 102) ('d', 103) ('e', 104)
```

- `x in series` → checks if Series index contains `x`

In [16]:
```
d = pd.Series([100,101,102,103,104], index=["a","b","c","d","e"])
pprint('102 in d', '"xxx" in d')
```

```
102 in d = False
"xxx" in d = False
```

Pandas DataFrame

- DataFrames are kind of specialized Python dictionaries $\{index_{typed\ \&\ ordered} \rightarrow series\}$ with a common row index
- Kind of *Series of Series* with a common row index
-
  - Three key attributes:
  - `values` : NumPy array
  - `index` and `columns` : array-like objects of type `pd.Index`

In [17]:
```
cities = ['California','Texas','Florida','New York']
population = pd.Series([39538223,29145505,21538187,20201249], index=cities)
area = pd.Series([423967, 695662, 170312, 141297], index=cities)
states = pd.DataFrame({'population':population, 'area':area})
states
```

Out[17]:

	population	area
California	39538223	423967
Texas	29145505	695662
Florida	21538187	170312
New York	20201249	141297

- The `index` attribute (*row index*) and `columns` attribute (*column index*) are of type `pd.Index`
- The `values` attribute (of type `np.ndarray`) contains the data

In [18]:
```
states.index
```

Out[18]:
```
Index(['California', 'Texas', 'Florida', 'New York'], dtype='object')
```

In [19]:
```
states.columns
```

Out[19]:
```
Index(['population', 'area'], dtype='object')
```

In [20]:
```
states.values
```

Out[20]:
```
array([[39538223,   423967],
       [29145505,   695662],
       [21538187,   170312],
       [20201249,   141297]])
```

A DataFrame can be constructed from a single series:

In [21]:
```
cities = ['California','Texas','Florida','New York']
population = pd.Series([39538223,29145505,21538187,20201249], index=cities)
states = pd.DataFrame(population, columns=['population'])
states
```

Out[21]:

	population
California	39538223
Texas	29145505
Florida	21538187
New York	20201249

A DataFrame can be constructed from a dictionary of Series:

In [22]:
```
cities = ['California','Texas','Florida','New York']
population = pd.Series([39538223,29145505,21538187,20201249], index=cities)
area = pd.Series([423967, 695662, 170312, 141297], index=cities)
states = pd.DataFrame({'population':population, 'area':area})
states
```

Out[22]:

	population	area
California	39538223	423967
Texas	29145505	695662
Florida	21538187	170312
New York	20201249	141297

A DataFrame can be constructed from list of dictionaries:

In [23]:

```
data = [
    {'population':39538223, 'area':423967},
    {'population':29145505, 'area':695662},
    {'population':21538187, 'area':170312},
    {'population':20201249, 'area':141297}
]
states = pd.DataFrame(data, index=["California","Texas","Florida","New York"])
states
```

Out[23]:

	population	area
California	39538223	423967
Texas	29145505	695662
Florida	21538187	170312
New York	20201249	141297

A DataFrame can be constructed from a two-dimensional NumPy array:

In [24]:

```
data = np.array([[39538223,   423967],
          [29145505,   695662],
          [21538187,   170312],
          [20201249,   141297]])
states = pd.DataFrame(data,
                      columns=["population","area"],
                      index=["California","Texas","Florida","New York"])
states
```

Out[24]:

	population	area
California	39538223	423967
Texas	29145505	695662
Florida	21538187	170312
New York	20201249	141297

A DataFrame can integrate indexes in different orders

In [25]:

```
cities1 = ['California','Texas','Florida','New York']
population = pd.Series([39538223,29145505,21538187,20201249], index=cities1)
cities2 = ['Texas','Florida','New York','California']
area = pd.Series([695662, 170312, 141297, 423967], index=cities2)
states = pd.DataFrame({'population':population, 'area':area})
states
```

Out[25]:

	population	area
California	39538223	423967
Florida	21538187	170312
New York	20201249	141297
Texas	29145505	695662

A DataFrame can integrate indexes with different values

- *Missing* values are filled with `NaN` s

In [26]:

```
cities1 = ['California','Texas','Florida']
population = pd.Series([39538223,29145505,21538187], index=cities1)
cities2 = ['Texas','Florida','New York']
area = pd.Series([695662, 170312, 141297], index=cities2)
states = pd.DataFrame({'population':population, 'area':area})
states
```

Out[26]:

	population	area
California	39538223.0	NaN
Florida	21538187.0	170312.0
New York	NaN	141297.0
Texas	29145505.0	695662.0

Pandas Index

- Kind of Immutable NumPy array
- Many NumPy attributes, indexable, sliceable, etc.

In [27]:

```
ind = pd.Index(['California', 'Texas', 'Florida'])
pprint('ind', 'ind[1]', 'ind[:2]', 'ind[[2,0,1]]', align=True, end='\n\n')
pprint('ind.size', 'ind.shape', 'ind.ndim', 'ind.dtype', align=True)
```

```
         ind = Index(['California', 'Texas', 'Florida'], dtype='object')
      ind[1] = 'Texas'
     ind[:2] = Index(['California', 'Texas'], dtype='object')
ind[[2,0,1]] = Index(['Florida', 'California', 'Texas'], dtype='object')

 ind.size = 3
ind.shape = (3,)
 ind.ndim = 1
ind.dtype = dtype('O')
```

In [28]:

```
ind = pd.Index([200, 1000, 300])
pprint('ind', 'ind[1]', 'ind[:2]', 'ind[[2,0,1]]', align=True, end='\n\n')
pprint('ind.size', 'ind.shape', 'ind.ndim', 'ind.dtype', align=True)
```

```
         ind = Index([200, 1000, 300], dtype='int64')
      ind[1] = 1000
     ind[:2] = Index([200, 1000], dtype='int64')
ind[[2,0,1]] = Index([300, 200, 1000], dtype='int64')

 ind.size = 3
ind.shape = (3,)
 ind.ndim = 1
ind.dtype = dtype('int64')
```

`pd.Index` follows many of the conventions of Python's `set`

- `idx1.union(idx2)` → combines elements from both Indexes
- `idx1.intersection(idx2)` → elements that are common to both Indexes
- `idx1.difference(idx2)` → elements in `idx1` that are not in `idx2`
- `idx1.symmetric_difference(idx2)` → elements in either, but not in both
- `idx1.equals(idx2)` → checks if they contain the same elements in the same order

In [29]:
```
idx1 = pd.Index([1,2,3,4,5])
idx2 = pd.Index([4,5,6,7])
pprint('idx1.union(idx2)', 'idx1.intersection(idx2)',
       'idx1.difference(idx2)', 'idx1.symmetric_difference(idx2)',
       'idx1.equals(idx2)', align=True)
```

```
             idx1.union(idx2) = Index([1, 2, 3, 4, 5, 6, 7], dtype='int64')
      idx1.intersection(idx2) = Index([4, 5], dtype='int64')
        idx1.difference(idx2) = Index([1, 2, 3], dtype='int64')
idx1.symmetric_difference(idx2) = Index([1, 2, 3, 6, 7], dtype='int64')
            idx1.equals(idx2) = False
```

Pandas I/O

- Powerfull and flexible IO collection of functions
  - Text-based files: CSV, TSV, plain text
  - Spreadsheet files: Excel, OpenOffice/LibreOffice
  - Web-based data: HTML
  - Structured data formats: JSON, XML
  - Relational Databases: SQL
  - Other formats: Pickle, HDF5, Parquet, ...
- In (`pd.read_...`): `pd.read_csv` , `pd.read_excel` , `pd.read_json` ,... `
- Out (`df.to_...`): `df.to_csv` , `df.to_excel` , `df.to_json` ,... `

In [30]:
```
#pd.read_
#df.to_
```

In [31]:
```
url = "https://raw.githubusercontent.com/pandas-dev/pandas/refs/heads/main/pandas/tests/io/da
pd.read_csv(url)
```

Out[31]:

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

In [32]:

```
#!pip install openpyxl
url = "https://github.com/pandas-dev/pandas/raw/refs/heads/main/pandas/tests/io/data/excel/te
pd.read_excel(url, index_col=0) # use first column as index
```

Out[32]:

	A	B	C	D
2000-01-03	0.980269	3.685731	-0.364217	-1.159738
2000-01-04	1.047916	-0.041232	-0.161812	0.212549
2000-01-05	0.498581	0.731168	-0.537677	1.346270
2000-01-06	1.120202	1.567621	0.003641	0.675253
2000-01-07	-0.487094	0.571455	-1.611639	0.103469
2000-01-10	0.836649	0.246462	0.588543	1.062782
2000-01-11	-0.157161	1.340307	1.195778	-1.097007

Indexing and Selection

In [33]:

```
cities = ['California', 'Texas', 'Florida', 'New York', 'Pennsylvania']
area = pd.Series([423967, 695662, 170312, 141297, 119280], index=cities)
population = pd.Series([39538223, 29145505, 21538187, 20201249, 13002700], index=cities)
gdp = pd.Series([3.9, 2.7, 1.3, 1.8, 1.0], index=cities) # Gross Domestic Product
df = pd.DataFrame({'area':area, 'population':population, 'GDP':gdp})
df
```

Out[33]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	20201249	1.8
Pennsylvania	119280	13002700	1.0

- Simple Indexing → column selection (**Series**)

In [34]:

```
df['area']
# KeyError: 0
```

```
#df[0]
```

Out[34]:
```
California      423967
Texas           695662
Florida         170312
New York        141297
Pennsylvania    119280
Name: area, dtype: int64
```

- Fancy Indexing → columns selection (**DataFrame**)

In [35]:
```
display( "df[['GDP','area']]", "df[['area']]")
```

Out[35]:

df[['GDP','area']]

	GDP	area
California	3.9	423967
Texas	2.7	695662
Florida	1.3	170312
New York	1.8	141297
Pennsylvania	1.0	119280

df[['area']]

	area
California	423967
Texas	695662
Florida	170312
New York	141297
Pennsylvania	119280

In [36]:
```
pprint("df['GDP']")
```

```
df['GDP'] = California      3.9
            Texas           2.7
            Florida         1.3
            New York        1.8
            Pennsylvania    1.0
            Name: GDP, dtype: float64
```

- Slicing → rows selection (**DataFrame**)

In [37]:
```
display('df[:2]', 'df[1:2]', 'df[2:2]')
```

Out[37]:

df[:2]

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7

df[1:2]

	area	population	GDP
Texas	695662	29145505	2.7

df[2:2]

	area	population	GDP

Combining columns & rows selection

- columns are selected with fancy indexes
- rows are selected with (position) slicing

In [38]:
```
display("df[['area','population']][:3]" , "df[:3][['area','population']]")
```

Out[38]:

df[['area','population']][:3]

	area	population
California	423967	39538223
Texas	695662	29145505
Florida	170312	21538187

df[:3][['area','population']]

	area	population
California	423967	39538223
Texas	695662	29145505
Florida	170312	21538187

Accessing the data through `df.values`

- `df.values` → homogeneous NumPy array
- Series values dtypes can be promoted

In [39]:
```
pprint('df.values')
pprint('df.values.dtype', 'df["area"].dtype',
       'df["population"].dtype', 'df["GDP"].dtype', align=True)
```

```
df.values = array([[4.2396700e+05, 3.9538223e+07, 3.9000000e+00],
                   [6.9566200e+05, 2.9145505e+07, 2.7000000e+00],
                   [1.7031200e+05, 2.1538187e+07, 1.3000000e+00],
                   [1.4129700e+05, 2.0201249e+07, 1.8000000e+00],
                   [1.1928000e+05, 1.3002700e+07, 1.0000000e+00]])
       df.values.dtype = dtype('float64')
      df["area"].dtype = dtype('int64')
df["population"].dtype = dtype('int64')
       df["GDP"].dtype = dtype('float64')
```

Masking with comparison operator

- Let `op` be an operator
- `Series op value` → broadcasted operation → Series
- `DataFrame op value` → broadcasted operation → DataFrame

In [40]:
```
pprint("df['GDP'] > 2")
```

```
df['GDP'] > 2 = California       True
                Texas            True
                Florida         False
                New York        False
                Pennsylvania    False
                Name: GDP, dtype: bool
```

In [41]:
```
display("df * 10" , "df > 2")
```

Out[41]:

df * 10

	area	population	GDP
California	4239670	395382230	39.0
Texas	6956620	291455050	27.0
Florida	1703120	215381870	13.0
New York	1412970	202012490	18.0
Pennsylvania	1192800	130027000	10.0

df > 2

	area	population	GDP
California	True	True	True
Texas	True	True	True
Florida	True	True	False
New York	True	True	False
Pennsylvania	True	True	False

Boolean Series/DataFrame can be used as indexes

- Boolean Series → select rows
- Boolean DataFrame → select elements (and fill with `NaN`)

In [42]:
```
display("df[df['GDP'] > 2]" , "df[df > 2]")
```

Out[42]:

df[df['GDP'] > 2]

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7

df[df > 2]

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	NaN
New York	141297	20201249	NaN
Pennsylvania	119280	13002700	NaN

Find the area for cities with `GDP>1` and `population<30000000`:

In [43]:
```
df[df['GDP'] > 1]
```

Out[43]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	20201249	1.8

In [44]:
```
df[(df['GDP']>1) & (df['population']<30000000)]
```

Out[44]:

	area	population	GDP
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	20201249	1.8

In [45]:
```
df[(df['GDP']>1) & (df['population']<30000000)]['area']
```

Out[45]:
```
Texas       695662
Florida     170312
New York    141297
Name: area, dtype: int64
```

Indexers: `.loc` and `.iloc`

- `.loc` → explicit indexing (and slicing)
- `.iloc` → implicit indexing (and slicing)
- NumPy style indexing
  - `.loc[i]` → row `i`
  - `.loc[i,j]` → row `i`, column `j`
  - Simple Indexing, Fancy Indexing and Slicing

In [46]:
```
df
```

Out[46]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	20201249	1.8
Pennsylvania	119280	13002700	1.0

In [47]:
```
df.loc['Florida']
```

Out[47]:
```
area             170312.0
population     21538187.0
GDP                   1.3
Name: Florida, dtype: float64
```

In [48]:
```
df.loc[['Florida','Texas']]
```

Out[48]:

	area	population	GDP
Florida	170312	21538187	1.3
Texas	695662	29145505	2.7

In [49]:
```
df.loc[:'Florida']
```

Out[49]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3

In [50]:
```
df.iloc[2]
```

Out[50]:
```
area             170312.0
population     21538187.0
GDP                   1.3
Name: Florida, dtype: float64
```

In [51]:
```
df.iloc[[2,1]]
```

Out[51]:

	area	population	GDP
Florida	170312	21538187	1.3
Texas	695662	29145505	2.7

In [52]:
```
df.iloc[:3]
```

Out[52]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3

In [53]:
```
df.loc['Florida','population']
```

Out[53]:
```
21538187
```

In [54]:
```
df.loc[['California','Florida'],'population']
```

```
Out[54]: California    39538223
         Florida       21538187
         Name: population, dtype: int64
```

```
In [55]: df.loc[['California','Florida'],:]
```

Out[55]:

	area	population	GDP
California	423967	39538223	3.9
Florida	170312	21538187	1.3

Using `.iloc` is similar to using `df.values`, but maintaining the DataFrame structure (vs. homogeneous NumPy array)

```
In [56]: df.iloc[:2,[0,2]]
```

Out[56]:

	area	GDP
California	423967	3.9
Texas	695662	2.7

```
In [57]: pprint("df.values[:2,[0,2]]" , "df.values[:2,[0,2]].dtype", align=True)
```

```
     df.values[:2,[0,2]] = array([[4.23967e+05, 3.90000e+00],
                                  [6.95662e+05, 2.70000e+00]])
df.values[:2,[0,2]].dtype = dtype('float64')
```

Modifying DataFrames Through Indexing

- The indexing can be used to modify a DataFrame
  - Modify values
  - Add/remove columns
  - Add/remove rows

Modifying DataFrame values

- Simple indexing → column assignment

```
In [58]: df2 = df.copy()
         df2['area'] = 0
         df2
```

Out[58]:

	area	population	GDP
California	0	39538223	3.9
Texas	0	29145505	2.7
Florida	0	21538187	1.3
New York	0	20201249	1.8
Pennsylvania	0	13002700	1.0

- Fancy Indexing → columns assignment

```
In [59]: df2 = df.copy()
         df2[['area','GDP']] = 0
```

```
df2
```

Out[59]:

	area	population	GDP
California	0	39538223	0
Texas	0	29145505	0
Florida	0	21538187	0
New York	0	20201249	0
Pennsylvania	0	13002700	0

- Slicing → rows assignment

In [60]:
```
df2 = df.copy()
df2[:2] = 0
df2
```

Out[60]:

	area	population	GDP
California	0	0	0.0
Texas	0	0	0.0
Florida	170312	21538187	1.3
New York	141297	20201249	1.8
Pennsylvania	119280	13002700	1.0

- Assigning to `df.values[i,j]` does not touch the dataframe

In [61]:
```
df2 = df.copy()
df2.values[:2,:2] = 0
df2
```

Out[61]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	20201249	1.8
Pennsylvania	119280	13002700	1.0

- Series masking (index is a boolean Series) → rows assignment

In [62]:
```
df2 = df.copy()
pprint('df2["GDP"]>2')
df2[df2['GDP']>2] = 0
df2
```

```
df2["GDP"]>2 = California        True
               Texas             True
               Florida          False
               New York         False
               Pennsylvania     False
               Name: GDP, dtype: bool
```

Out[62]:

	area	population	GDP
California	0	0	0.0
Texas	0	0	0.0
Florida	170312	21538187	1.3
New York	141297	20201249	1.8
Pennsylvania	119280	13002700	1.0

- DataFrame masking (index is a boolean DataFrame) → *elements* assignment

In [63]:
```
df2 = df.copy()
pprint('df2>2')
df2[df2>2] = 0
df2
```

```
df2>2 =                 area  population    GDP
        California      True        True   True
        Texas           True        True   True
        Florida         True        True  False
        New York        True        True  False
        Pennsylvania    True        True  False
```

Out[63]:

	area	population	GDP
California	0	0	0.0
Texas	0	0	0.0
Florida	0	0	1.3
New York	0	0	1.8
Pennsylvania	0	0	1.0

- `.loc` and `.iloc` → *subset* assignment

In [64]:
```
df2 = df.copy()
df2.loc[['California','New York'],'population':] = 0
df2
```

Out[64]:

	area	population	GDP
California	423967	0	0.0
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	0	0.0
Pennsylvania	119280	13002700	1.0

In [65]:
```
df2 = df.copy()
df2.iloc[[0,3],1:] = 0
df2
```

Out[65]:

	area	population	GDP
California	423967	0	0.0
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	0	0.0
Pennsylvania	119280	13002700	1.0

Adding/Removing columns

- **Add**: `df[new_index] = value`
- **Remove**: `del df[index]` or `df.drop(index, axis=1, inplace=True)`

In [66]:

```
# add column 'density'
df2 = df.copy()
df2['density'] = df2['population'] / df2['area']
df2
```

Out[66]:

	area	population	GDP	density
California	423967	39538223	3.9	93.257784
Texas	695662	29145505	2.7	41.896072
Florida	170312	21538187	1.3	126.463121
New York	141297	20201249	1.8	142.970120
Pennsylvania	119280	13002700	1.0	109.009893

In [67]:

```
# remove column 'population'
df2 = df.copy()
del df2['population']
df2
```

Out[67]:

	area	GDP
California	423967	3.9
Texas	695662	2.7
Florida	170312	1.3
New York	141297	1.8
Pennsylvania	119280	1.0

In [68]:

```
# remove column 'population'
df2 = df.copy()
df2.drop('population', axis=1, inplace=True)
df2
```

Out[68]:

	area	GDP
California	423967	3.9
Texas	695662	2.7
Florida	170312	1.3
New York	141297	1.8
Pennsylvania	119280	1.0

In [69]:

```
# remove columns ['area','population']
df2 = df.copy()
```

```
df2.drop(['area','population'], axis=1, inplace=True)
df2
```

Out[69]:

	GDP
California	3.9
Texas	2.7
Florida	1.3
New York	1.8
Pennsylvania	1.0

Adding/Removing rows

- **Add**: `df.loc[new_index] = value` (WARNING → homogeneous DataFrame)
- **Remove**: `df.drop(index, axis=0, inplace=True)`

In [70]:

```
# add row 'chicago'
df2 = df.copy()
df2.loc['Chicago'] = [111111,22222222,2.0]
df2
```

Out[70]:

	area	population	GDP
California	423967.0	39538223.0	3.9
Texas	695662.0	29145505.0	2.7
Florida	170312.0	21538187.0	1.3
New York	141297.0	20201249.0	1.8
Pennsylvania	119280.0	13002700.0	1.0
Chicago	111111.0	22222222.0	2.0

In [71]:

```
# remove row 'New York'
df2 = df.copy()
df2.drop('New York', axis=0, inplace=True)
df2
```

Out[71]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
Pennsylvania	119280	13002700	1.0

In [72]:

```
# remove rows ['California','New York']
df2 = df.copy()
df2.drop(['California','New York'], axis=0, inplace=True)
df2
```

Out[72]:

	area	population	GDP
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
Pennsylvania	119280	13002700	1.0

Operating on Data

- Arithmetic operators and NumPy functions can be applied to Series/DataFrames
- Indexes are preserved
- Binary operations/functions align the indexes
  - Can manage incomplete data inserting `NaN` s
- DataFrame and Series operation have broadcasting property

Index Preservation

In [73]:
```
df
```

Out[73]:

	area	population	GDP
California	423967	39538223	3.9
Texas	695662	29145505	2.7
Florida	170312	21538187	1.3
New York	141297	20201249	1.8
Pennsylvania	119280	13002700	1.0

In [74]:
```
df * 10
```

Out[74]:

	area	population	GDP
California	4239670	395382230	39.0
Texas	6956620	291455050	27.0
Florida	1703120	215381870	13.0
New York	1412970	202012490	18.0
Pennsylvania	1192800	130027000	10.0

In [75]:
```
np.log(df[['area','population']])
```

Out[75]:

	area	population
California	12.957411	17.492778
Texas	13.452619	17.187811
Florida	12.045387	16.885338
New York	11.858619	16.821255
Pennsylvania	11.689229	16.380668

Python operators have their equivalent Pandas object methods:

Python operator	Pandas method(s)
`+`	`add`
`-`	`sub`, `subtract`
`*`	`mul`, `multiply`
`/`	`truediv`, `div`, `divide`
`//`	`floordiv`
`%`	`mod`
`**`	`pow`

Index Alignment

In [76]:
```
x = pd.Series({'A': 10,'B': 20})
y = pd.Series({'B': 4, 'A': 5})
x / y
```

Out[76]:
```
A    2.0
B    5.0
dtype: float64
```

In [77]:
```
x = pd.Series({'A': 10,'B': 20, 'C':30})
y = pd.Series({'B': 4, 'C': 5, 'D':3})
x / y
```

Out[77]:
```
A    NaN
B    5.0
C    6.0
D    NaN
dtype: float64
```

In [78]:
```
df1 = pd.DataFrame({
    'first':pd.Series([1,2],index=["A","B"]),
    'second':pd.Series([1,2],index=["A","B"])})
df2 = pd.DataFrame({
    'first':pd.Series([3,2],index=["A","C"]),
    'second':pd.Series([2,4],index=["A","C"])})
```

In [79]:
```
display("df1", "df2" , "df1 + df2")
```

Out[79]:

df1

	first	second
A	1	1
B	2	2

df2

	first	second
A	3	2
C	2	4

df1 + df2

	first	second
A	4.0	3.0
B	NaN	NaN
C	NaN	NaN

Pandas arithmetic functions have a `fill_value` parameter to be used in place of missing entries:

In [80]:
```
df1.add(df2)
```

Out[80]:

	first	second
A	4.0	3.0
B	NaN	NaN
C	NaN	NaN

In [81]:
```
df1.add(df2, fill_value=0)
```

Out[81]:

	first	second
A	4.0	3.0
B	2.0	2.0
C	2.0	4.0

In [82]:
```
df1.loc['C']=0
df2.loc['B']=0
display("df1" , "df2" , "df1+df2")
```

Out[82]:

df1

	first	second
A	1	1
B	2	2
C	0	0

df2

	first	second
A	3	2
C	2	4
B	0	0

df1+df2

	first	second
A	4	3
B	2	2
C	2	4

Operations Between DataFrames and Series

- Broadcasting, *similar* to NumPy
  - Limited to row-wise

In [83]:
```
ints = np.random.randint(0,10,(3,4))
df = pd.DataFrame(ints, columns=['A','B','C','D'], index=['x','y','z'])
df
```

Out[83]:

	A	B	C	D
x	4	0	8	5
y	6	9	2	0
z	9	1	0	7

In [84]:
```
display("df" , "df - df.loc['x']" , "df.sub(df.loc['x'], axis=1)")
```

Out[84]:

df

	A	B	C	D
x	4	0	8	5
y	6	9	2	0
z	9	1	0	7

df - df.loc['x']

	A	B	C	D
x	0	0	0	0
y	2	9	-6	-5
z	5	1	-8	2

df.sub(df.loc['x'], axis=1)

	A	B	C	D
x	0	0	0	0
y	2	9	-6	-5
z	5	1	-8	2

In [85]:
```
df
```

Out[85]:

	A	B	C	D
x	4	0	8	5
y	6	9	2	0
z	9	1	0	7

In [86]:
```python
# Broadcasting rules...
display("df - df['A']" , "df.sub(df['A'], axis=0)")
```

Out[86]:

df - df['A']

	A	B	C	D	x	y	z
x	NaN	NaN	NaN	NaN	NaN	NaN	NaN
y	NaN	NaN	NaN	NaN	NaN	NaN	NaN
z	NaN	NaN	NaN	NaN	NaN	NaN	NaN

df.sub(df['A'], axis=0)

	A	B	C	D
x	0	-4	4	1
y	0	3	-4	-6
z	0	-8	-9	-2

`pd.DataFrame(df['A'])` is a single column dataframe, but there is no broadcasting between dataframes...

In [87]:
```python
display("pd.DataFrame(df['A'])" , "df - pd.DataFrame(df['A'])")
```

Out[87]:

pd.DataFrame(df['A'])

	A
x	4
y	6
z	9

df - pd.DataFrame(df['A'])

	A	B	C	D
x	0	NaN	NaN	NaN
y	0	NaN	NaN	NaN
z	0	NaN	NaN	NaN

Handling Missing Data

Pandas use *Sentinel Values* to handle not available (NA) values:

- `None`, `np.nan` and `pd.NA`
  - Integer data: `pd.NA`
  - Floating point data: `np.nan` and `pd.NA`
  - General object data: `None`, `np.nan` and `pd.NA`
- By default, in numeric data, `None` → `np.nan` (floating point)

In [88]:
```python
s = pd.Series([None,2,3])
pprint('s', 's[0]', 'type(s[0])', align=True)
```

```
          s = 0     NaN
              1     2.0
              2     3.0
              dtype: float64
       s[0] = nan
 type(s[0]) = <class 'numpy.float64'>
```

In [89]:
```python
s = pd.Series([np.nan,2,3])
pprint('s', 's[0]', 'type(s[0])', align=True)
```

```
        s = 0    NaN
            1    2.0
            2    3.0
            dtype: float64
     s[0] = nan
type(s[0]) = <class 'numpy.float64'>
```

In [90]:
```
s = pd.Series([pd.NA,2,3])
pprint('s', 's[0]', 'type(s[0])', align=True)
```

```
        s = 0    <NA>
            1       2
            2       3
            dtype: object
     s[0] = <NA>
type(s[0]) = <class 'pandas._libs.missing.NAType'>
```

In [91]:
```
s = pd.Series([None,2,3], dtype='Int64')
pprint('s', 's[0]', 'type(s[0])', align=True)
```

```
        s = 0    <NA>
            1       2
            2       3
            dtype: Int64
     s[0] = <NA>
type(s[0]) = <class 'pandas._libs.missing.NAType'>
```

In [92]:
```
s = pd.Series([np.nan,2,3], dtype='Int64')
pprint('s', 's[0]', 'type(s[0])', align=True)
```

```
        s = 0    <NA>
            1       2
            2       3
            dtype: Int64
     s[0] = <NA>
type(s[0]) = <class 'pandas._libs.missing.NAType'>
```

In [93]:
```
pprint('pd.Series([None,"a",123])')
```

```
pd.Series([None,"a",123]) = 0    None
                            1       a
                            2     123
                            dtype: object
```

In [94]:
```
pprint('pd.Series([np.nan,"a",123])')
```

```
pd.Series([np.nan,"a",123]) = 0    NaN
                              1      a
                              2    123
                              dtype: object
```

In [95]:
```
pprint('pd.Series([pd.NA,"a",123])')
```

```
pd.Series([pd.NA,"a",123]) = 0    <NA>
                             1       a
                             2     123
                             dtype: object
```

Table of upcasting conventions in Pandas when NA values are introduced:

Typeclass	Conversion when storing NAs	NA sentinel value
`floating`	No change	`np.nan`
`object`	No change	`None` or `np.nan`
`integer`	Cast to `float64`	`np.nan`

Typeclass	Conversion when storing NAs	NA sentinel value
`boolean`	Cast to `object`	`None` or `np.nan`

Ignoring Null values

- Most Numpy functions are not `nan` -aware (generate `nan`)
  - `nan` -aware NumPy functions (ignore `nan` s):
    - `np.nansum`
    - `np.nanmin`
    - `np.nanmax`
  - NumPy does not handle `pd.NA` → **ERROR**
- Pandas functions are `NaN` and `NA` aware (ignore `nan` s)

In [96]:
```
s = pd.Series([1,2,None,3,4])
pprint('s.values',
       's.values.sum()', 's.values.min()', 's.values.max()',
       'np.sum(s.values)', 'np.min(s.values)', 'np.max(s.values)',
       'np.nansum(s.values)', 'np.nanmin(s.values)', 'np.nanmax(s.values)',
       's.sum()', 's.min()', 's.max()', align=True)
```

```
           s.values = array([ 1.,  2., nan,  3.,  4.])
     s.values.sum() = nan
     s.values.min() = nan
     s.values.max() = nan
   np.sum(s.values) = nan
   np.min(s.values) = nan
   np.max(s.values) = nan
np.nansum(s.values) = 10.0
np.nanmin(s.values) = 1.0
np.nanmax(s.values) = 4.0
            s.sum() = 10.0
            s.min() = 1.0
            s.max() = 4.0
```

In [97]:
```
s = pd.Series([1,2,pd.NA,3,4])
pprint('s.values',
       's.sum()', 's.min()', 's.max()', align=True)
# ERROR!
#pprint('s.values.sum()', 's.values.min()', 's.values.max()',
#        'np.sum(s.values)', 'np.min(s.values)', 'np.max(s.values)',
#        'np.nansum(s.values)', 'np.nanmin(s.values)', 'np.nanmax(s.values)')
```

```
s.values = array([1, 2, <NA>, 3, 4], dtype=object)
 s.sum() = 10
 s.min() = 1
 s.max() = 4
```

Detecting Null values

- `isnull` → boolean mask (`True` / `False`) where Null values
- `notnull` → opposite of `isnull`

In [98]:
```
s = pd.Series([1,2,None,3,4])
pprint('s.isnull()', 's.notnull()', sep="\n\n", align=True)
```

```
s.isnull() = 0    False
             1    False
             2     True
             3    False
             4    False
             dtype: bool

s.notnull() = 0     True
              1     True
              2    False
              3     True
              4     True
              dtype: bool
```

In [99]:
```
s[s.notnull()]
```

Out[99]:
```
0    1.0
1    2.0
3    3.0
4    4.0
dtype: float64
```

Dropping Null values

- `dropna` → copy with the null values removed
  - Series: remove Null values
  - DataFrame: remove rows/columns containing Null values
- `inplace` parameter: bool, default False
  - If True, remove/fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

In [100…
```
s = pd.Series([1,2,None,3,4])
s.dropna()
```

Out[100…
```
0    1.0
1    2.0
3    3.0
4    4.0
dtype: float64
```

In [101…
```
pprint('s',end='\n\n')
s.dropna(inplace=True)
pprint('s')
```

```
s = 0    1.0
    1    2.0
    2    NaN
    3    3.0
    4    4.0
    dtype: float64

s = 0    1.0
    1    2.0
    3    3.0
    4    4.0
    dtype: float64
```

In [102…
```
a = np.arange(15,dtype='float64').reshape(3,5)
a[(0,2,2),(3,0,2)] = np.nan
df = pd.DataFrame(a)
df
```

Out[102...

	0	1	2	3	4
0	0.0	1.0	2.0	NaN	4.0
1	5.0	6.0	7.0	8.0	9.0
2	NaN	11.0	NaN	13.0	14.0

In [103...

```
df.dropna() # df.dropna(axis=0)
```

Out[103...

	0	1	2	3	4
1	5.0	6.0	7.0	8.0	9.0

In [104...

```
df.dropna(axis=1)
```

Out[104...

	1	4
0	1.0	4.0
1	6.0	9.0
2	11.0	14.0

Filling Null values

- `fillna` → copy with the null values replaced
- `inplace` parameter: bool, default False
  - If True, remove/fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).
- **DEPRECATED** `method` parameter: { `bfill` , `ffill` , None}, default None
  - `ffill` → *forward fill*, propagate the previous value forward
  - `bfill` → *back fill*, propagate the next values backward
- use `data.ffill()` and `data.bfill()` instead
  - `axis` parameter: axis along which forward/back fill

In [105...

```
s = pd.Series([1, None, 2, None, 3], index=list('abcde'), dtype='Int64')
pprint('s', 's.fillna(0)', 's.ffill()', 's.bfill()', align=True)
```

```
          s = a       1
              b    <NA>
              c       2
              d    <NA>
              e       3
              dtype: Int64
s.fillna(0) = a    1
              b    0
              c    2
              d    0
              e    3
              dtype: Int64
  s.ffill() = a    1
              b    1
              c    2
              d    2
              e    3
              dtype: Int64
  s.bfill() = a    1
              b    2
              c    2
              d    3
              e    3
              dtype: Int64
```

In [106…

```python
a = np.arange(15,dtype='float64').reshape(3,5)
a[(0,2,2),(3,0,2)] = np.nan
df = pd.DataFrame(a)

display("df" , "df.fillna(0)")
```

Out[106…

df

	0	1	2	3	4
0	0.0	1.0	2.0	NaN	4.0
1	5.0	6.0	7.0	8.0	9.0
2	NaN	11.0	NaN	13.0	14.0

df.fillna(0)

	0	1	2	3	4
0	0.0	1.0	2.0	0.0	4.0
1	5.0	6.0	7.0	8.0	9.0
2	0.0	11.0	0.0	13.0	14.0

In [107…

```python
df
```

Out[107…

	0	1	2	3	4
0	0.0	1.0	2.0	NaN	4.0
1	5.0	6.0	7.0	8.0	9.0
2	NaN	11.0	NaN	13.0	14.0

In [108…

```python
display("df.ffill()" , "df.ffill(axis=1)")
```

Out[108…

df.ffill()

	0	1	2	3	4
0	0.0	1.0	2.0	NaN	4.0
1	5.0	6.0	7.0	8.0	9.0
2	5.0	11.0	7.0	13.0	14.0

df.ffill(axis=1)

	0	1	2	3	4
0	0.0	1.0	2.0	2.0	4.0
1	5.0	6.0	7.0	8.0	9.0
2	NaN	11.0	11.0	13.0	14.0

In [109…
```
df
```

Out[109…

	0	1	2	3	4
0	0.0	1.0	2.0	NaN	4.0
1	5.0	6.0	7.0	8.0	9.0
2	NaN	11.0	NaN	13.0	14.0

In [110…
```
display("df.bfill()" , "df.bfill(axis=1)")
```

Out[110…

df.bfill()

	0	1	2	3	4
0	0.0	1.0	2.0	8.0	4.0
1	5.0	6.0	7.0	8.0	9.0
2	NaN	11.0	NaN	13.0	14.0

df.bfill(axis=1)

	0	1	2	3	4
0	0.0	1.0	2.0	4.0	4.0
1	5.0	6.0	7.0	8.0	9.0
2	11.0	11.0	13.0	13.0	14.0

Concatenating Datasets

In [111…
```
def make_df(col_index,row_index):
    """Quickly make a DataFrame"""
    data = {c: [str(c) + str(r) for r in row_index] for c in col_index}
    return pd.DataFrame(data, index=list(row_index), columns=list(col_index))

# example DataFrame
display("make_df('ABCDEF',range(3))" , "make_df('ABCDEF','xyz')")
```

Out[111…

make_df('ABCDEF',range(3))

	A	B	C	D	E	F
0	A0	B0	C0	D0	E0	F0
1	A1	B1	C1	D1	E1	F1
2	A2	B2	C2	D2	E2	F2

make_df('ABCDEF','xyz')

	A	B	C	D	E	F
x	Ax	Bx	Cx	Dx	Ex	Fx
y	Ay	By	Cy	Dy	Ey	Fy
z	Az	Bz	Cz	Dz	Ez	Fz

`pd.concat()`

- Similar to NumPy `concatenate`

```
pd.concat(objs, axis=0, join='outer', ignore_index=False, keys=None,
          levels=None, names=None, verify_integrity=False,
          sort=False, copy=True)
```

In [112…
```
s1 = pd.Series(['A', 'B', 'C'], index=[1, 2, 3])
s2 = pd.Series(['D', 'E', 'F'], index=[4, 5, 6])
pd.concat([s1, s2])
```

Out[112…
```
1    A
2    B
3    C
4    D
5    E
6    F
dtype: object
```

In [113…
```python
s1 = pd.Series(['A', 'B', 'C'], index=[1, 2, 3])
s2 = pd.Series(['D', 'E', 'F'], index=[1, 2, 3])
pd.concat([s1, s2], axis=1)
```

Out[113…

	0	1
1	A	D
2	B	E
3	C	F

In [114…
```python
df1 = make_df('AB', 'uv')
df2 = make_df('AB', 'xy')
display('df1', 'df2', 'pd.concat([df1, df2])')
```

Out[114…

df1

	A	B
u	Au	Bu
v	Av	Bv

df2

	A	B
x	Ax	Bx
y	Ay	By

pd.concat([df1, df2])

	A	B
u	Au	Bu
v	Av	Bv
x	Ax	Bx
y	Ay	By

In [115…
```python
df1 = make_df('AB', 'xy')
df2 = make_df('CD', 'xy')
display('df1', 'df2', 'pd.concat([df1, df2], axis=1)')
```

Out[115…

df1

	A	B
x	Ax	Bx
y	Ay	By

df2

	C	D
x	Cx	Dx
y	Cy	Dy

pd.concat([df1, df2], axis=1)

	A	B	C	D
x	Ax	Bx	Cx	Dx
y	Ay	By	Cy	Dy

- **Index preservation**: `pd.concatenate` *preserves* indices (result could have duplicate indices)

In [116…
```python
df1 = make_df('AB', 'xy')
df2 = make_df('AB', 'xy')
df_axis0 = pd.concat([df1, df2])
df_axis1 = pd.concat([df1, df2], axis=1)
display('df1', 'df2' , 'df_axis0' , 'df_axis1')
```

Out[116…

df1

	A	B
x	Ax	Bx
y	Ay	By

df2

	A	B
x	Ax	Bx
y	Ay	By

df_axis0

	A	B
x	Ax	Bx
y	Ay	By
x	Ax	Bx
y	Ay	By

df_axis1

	A	B	A	B
x	Ax	Bx	Ax	Bx
y	Ay	By	Ay	By

- `verify_integrity=True` prevents index duplication (raises `ValueError`)

In [117…

```
df1 = make_df('AB', 'xy')
df2 = make_df('AB', 'xy')
try:
    pd.concat([df1, df2], verify_integrity=True)
except ValueError as e:
    print("axis=0 ValueError:", e)
try:
    pd.concat([df1, df2], axis=1, verify_integrity=True)
except ValueError as e:
    print("axis=1 ValueError:", e)
display('df1', 'df2')
```

```
axis=0 ValueError: Indexes have overlapping values: Index(['x', 'y'], dtype='object')
axis=1 ValueError: Indexes have overlapping values: Index(['A', 'B'], dtype='object')
```

Out[117…

df1

	A	B
x	Ax	Bx
y	Ay	By

df2

	A	B
x	Ax	Bx
y	Ay	By

- `ignore_index=True` ignores overlapped indexes (replaced by `RangeIndex`)

In [118…

```
df1 = make_df('AB', 'xy')
df2 = make_df('AB', 'xy')
df_axis0 = pd.concat([df1, df2], ignore_index=True)
df_axis1 = pd.concat([df1, df2], axis=1, ignore_index=True)
pprint('df_axis0.index', 'df_axis0.columns',
       'df_axis1.index', 'df_axis1.columns', align=True)
display('df1', 'df2' , 'df_axis0' , 'df_axis1')
```

```
  df_axis0.index = RangeIndex(start=0, stop=4, step=1)
df_axis0.columns = Index(['A', 'B'], dtype='object')
  df_axis1.index = Index(['x', 'y'], dtype='object')
df_axis1.columns = RangeIndex(start=0, stop=4, step=1)
```

Out[118…

df1

	A	B
x	Ax	Bx
y	Ay	By

df2

	A	B
x	Ax	Bx
y	Ay	By

df_axis0

	A	B
0	Ax	Bx
1	Ay	By
2	Ax	Bx
3	Ay	By

df_axis1

	0	1	2	3
x	Ax	Bx	Ax	Bx
y	Ay	By	Ay	By

- `join="outer"` (default): could create Null data
- `join="inner` : avoids Null data
  - `axis=0` → removes columns
  - `axis=1` → removes rows

In [119…

```
df1 = make_df('ABC', [1,2])
df2 = make_df('BCD', [3,4])
display('df1', 'df2')
```

Out[119…

df1

	A	B	C
1	A1	B1	C1
2	A2	B2	C2

df2

	B	C	D
3	B3	C3	D3
4	B4	C4	D4

In [120…

```
df_outer = pd.concat([df1, df2])
df_inner = pd.concat([df1, df2], join='inner')
display('df_outer', 'df_inner')
```

Out[120…

df_outer

	A	B	C	D
1	A1	B1	C1	NaN
2	A2	B2	C2	NaN
3	NaN	B3	C3	D3
4	NaN	B4	C4	D4

df_inner

	B	C
1	B1	C1
2	B2	C2
3	B3	C3
4	B4	C4

In [121…

```
df1 = make_df('AB', [1,2,3])
df2 = make_df('CD', [2,3,4])
display('df1', 'df2')
```

Out[121…

df1

	A	B
1	A1	B1
2	A2	B2
3	A3	B3

df2

	C	D
2	C2	D2
3	C3	D3
4	C4	D4

In [122…
```
df_outer = pd.concat([df1, df2], axis=1)
df_inner = pd.concat([df1, df2], axis=1, join='inner')
display('df_outer', 'df_inner')
```

Out[122…

df_outer

	A	B	C	D
1	A1	B1	NaN	NaN
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	NaN	NaN	C4	D4

df_inner

	A	B	C	D
2	A2	B2	C2	D2
3	A3	B3	C3	D3

Merging Datasets

`pd.merge()`

- Merges two Series/DataFrame
- *Common* columns are used as merging keys

```
pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None,
         left_index=False, right_index=False, sort=False,
         suffixes=('_x', '_y'), copy=None, indicator=False, validate=None)
```

In [123…
```
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa'],
                    'group': ['Accounting', 'Engineering','Engineering']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake'],
                    'hire_date': [2004, 2008, 2012]})
display('df1', 'df2')
```

Out[123…

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering

df2

	employee	hire_date
0	Lisa	2004
1	Bob	2008
2	Jake	2012

In [124…
```
pd.merge(df1, df2)
```

Out[124…

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004

In [125…
```
df1 = pd.merge(df1, df2)
df2 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'],
                    'supervisor': ['Carly', 'Guido', 'Steve']})
display('df1', 'df2')
```

Out[125…

df1

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004

df2

	group	supervisor
0	Accounting	Carly
1	Engineering	Guido
2	HR	Steve

In [126…

```
pd.merge(df1, df2)
```

Out[126…

	employee	group	hire_date	supervisor
0	Bob	Accounting	2008	Carly
1	Jake	Engineering	2012	Guido
2	Lisa	Engineering	2004	Guido

In [127…

```
df2 = pd.DataFrame({'group': ['Accounting', 'Accounting', 'Engineering', 'Engineering'],
                    'skills': ['math', 'spreadsheets', 'software', 'math']})
display('df1', 'df2')
```

Out[127…

df1

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004

df2

	group	skills
0	Accounting	math
1	Accounting	spreadsheets
2	Engineering	software
3	Engineering	math

In [128…

```
pd.merge(df1, df2)
```

Out[128…

	employee	group	hire_date	skills
0	Bob	Accounting	2008	math
1	Bob	Accounting	2008	spreadsheets
2	Jake	Engineering	2012	software
3	Jake	Engineering	2012	math
4	Lisa	Engineering	2004	software
5	Lisa	Engineering	2004	math

- `on=column_name` → use column as key
- `left_on=name1`, `right_on=name2` → use columns as key

In [129…

```
df2 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'], 'salary': [70000, 80000, 120000, '
display('df1', 'df2')
```

Out[129...

df1

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004

df2

	name	salary
0	Bob	70000
1	Jake	80000
2	Lisa	120000
3	Sue	90000

In [130...

```
pd.merge(df1, df2, left_on="employee", right_on="name")
```

Out[130...

	employee	group	hire_date	name	salary
0	Bob	Accounting	2008	Bob	70000
1	Jake	Engineering	2012	Jake	80000
2	Lisa	Engineering	2004	Lisa	120000

Using `left_on=name1` , `right_on=name2` implies a redundant column

In [131...

```
pd.merge(df1, df2, left_on="employee", right_on="name")
```

Out[131...

	employee	group	hire_date	name	salary
0	Bob	Accounting	2008	Bob	70000
1	Jake	Engineering	2012	Jake	80000
2	Lisa	Engineering	2004	Lisa	120000

In [132...

```
pd.merge(df1, df2, left_on="employee", right_on="name").drop('name', axis=1)
```

Out[132...

	employee	group	hire_date	salary
0	Bob	Accounting	2008	70000
1	Jake	Engineering	2012	80000
2	Lisa	Engineering	2004	120000

- `left_index=True` , `right_index=True` → use indexes as key

In [133...

```
df2 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa'],
                    'salary': [70000, 80000, 120000]})
df2.set_index('name', inplace=True)
display('df1', 'df2')
```

Out[133...

df1

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004

df2

	salary
name	
Bob	70000
Jake	80000
Lisa	120000

In [134...

```
pd.merge(df1, df2, left_on='employee', right_index=True)
```

Out[134…

	employee	group	hire_date	salary
0	Bob	Accounting	2008	70000
1	Jake	Engineering	2012	80000
2	Lisa	Engineering	2004	120000

- `df1.join(df2)` → index based merging
  - `pd.merge(df1, df2, left_index=True, right_index=True)`

In [135…

```
df1.set_index('employee', inplace=True)
display('df1', 'df2')
```

Out[135…

df1

	group	hire_date
employee		
Bob	Accounting	2008
Jake	Engineering	2012
Lisa	Engineering	2004

df2

	salary
name	
Bob	70000
Jake	80000
Lisa	120000

In [136…

```
df1.join(df2)
```

Out[136…

	group	hire_date	salary
employee			
Bob	Accounting	2008	70000
Jake	Engineering	2012	80000
Lisa	Engineering	2004	120000

- `how='inner'` (default) → intersection

In [137…

```
df1 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary', 'Adam'],
                    'food': ['fish', 'beans', 'bread' , 'fish']})
df2 = pd.DataFrame({'name': ['Mary', 'Joseph', 'Peter' , 'Alice'],
                    'drink': ['wine', 'beer' , 'water' , 'beer']})
display('df1', 'df2', 'pd.merge(df1, df2)')
```

Out[137…

df1

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread
3	Adam	fish

df2

	name	drink
0	Mary	wine
1	Joseph	beer
2	Peter	water
3	Alice	beer

pd.merge(df1, df2)

	name	food	drink
0	Peter	fish	water
1	Mary	bread	wine

- `how='outer'` → union (Null values)

In [138…

```
display('df1', 'df2', 'pd.merge(df1, df2, how="outer")')
```

Out[138…

df1

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread
3	Adam	fish

df2

	name	drink
0	Mary	wine
1	Joseph	beer
2	Peter	water
3	Alice	beer

pd.merge(df1, df2, how="outer")

	name	food	drink
0	Adam	fish	NaN
1	Alice	NaN	beer
2	Joseph	NaN	beer
3	Mary	bread	wine
4	Paul	beans	NaN
5	Peter	fish	water

- `how='left'` → keep left key (Null values)

In [139…

```
display('df1', 'df2', 'pd.merge(df1, df2, how="left")')
```

Out[139…

df1

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread
3	Adam	fish

df2

	name	drink
0	Mary	wine
1	Joseph	beer
2	Peter	water
3	Alice	beer

pd.merge(df1, df2, how="left")

	name	food	drink
0	Peter	fish	water
1	Paul	beans	NaN
2	Mary	bread	wine
3	Adam	fish	NaN

- `how='right'` → keep left key (Null values)

In [140…

```
display('df1', 'df2', 'pd.merge(df1, df2, how="right")')
```

Out[140…

df1

	name	food
0	Peter	fish
1	Paul	beans
2	Mary	bread
3	Adam	fish

df2

	name	drink
0	Mary	wine
1	Joseph	beer
2	Peter	water
3	Alice	beer

pd.merge(df1, df2, how="right")

	name	food	drink
0	Mary	bread	wine
1	Joseph	NaN	beer
2	Peter	fish	water
3	Alice	NaN	beer

Aggregation and Grouping

Planets Data

Information on exoplanets (planets that orbit a star other than the Sun) that astronomers have discovered.

In [141…

```
import seaborn as sns
planets = sns.load_dataset('planets')
planets.shape
```

Out[141... (1035, 6)

In [142...
```
planets.head(10)  #planets[:10]
```

Out[142...

	method	number	orbital_period	mass	distance	year
0	Radial Velocity	1	269.300	7.10	77.40	2006
1	Radial Velocity	1	874.774	2.21	56.95	2008
2	Radial Velocity	1	763.000	2.60	19.84	2011
3	Radial Velocity	1	326.030	19.40	110.62	2007
4	Radial Velocity	1	516.220	10.50	119.47	2009
5	Radial Velocity	1	185.840	4.80	76.39	2008
6	Radial Velocity	1	1773.400	4.64	18.15	2002
7	Radial Velocity	1	798.500	NaN	21.41	1996
8	Radial Velocity	1	993.300	10.30	73.10	2008
9	Radial Velocity	2	452.800	1.99	74.79	2010

In [143...
```
planets.dropna(inplace=True)
print(planets.shape)
planets.head(10)
```

(498, 6)

Out[143...

	method	number	orbital_period	mass	distance	year
0	Radial Velocity	1	269.300	7.10	77.40	2006
1	Radial Velocity	1	874.774	2.21	56.95	2008
2	Radial Velocity	1	763.000	2.60	19.84	2011
3	Radial Velocity	1	326.030	19.40	110.62	2007
4	Radial Velocity	1	516.220	10.50	119.47	2009
5	Radial Velocity	1	185.840	4.80	76.39	2008
6	Radial Velocity	1	1773.400	4.64	18.15	2002
8	Radial Velocity	1	993.300	10.30	73.10	2008
9	Radial Velocity	2	452.800	1.99	74.79	2010
10	Radial Velocity	2	883.000	0.86	74.79	2010

Aggregation functions

Some built-in Pandas aggregations:

Aggregation	Description
`count()`	Total number of items
`first()`, `last()`	First and last item
`mean()`, `median()`	Mean and median
`min()`, `max()`	Minimum and maximum
`std()`, `var()`	Standard deviation and variance
`mad()`	Mean absolute deviation
`sum()`, `prod()`	Sum and product of all items

In [144…
```
planets = sns.load_dataset('planets')
df = planets.dropna().drop(['method','number'], axis=1)
print(df.shape)
pprint('df.min()', 'df.max()', 'df.mean()', 'df.std()', align=True)
```

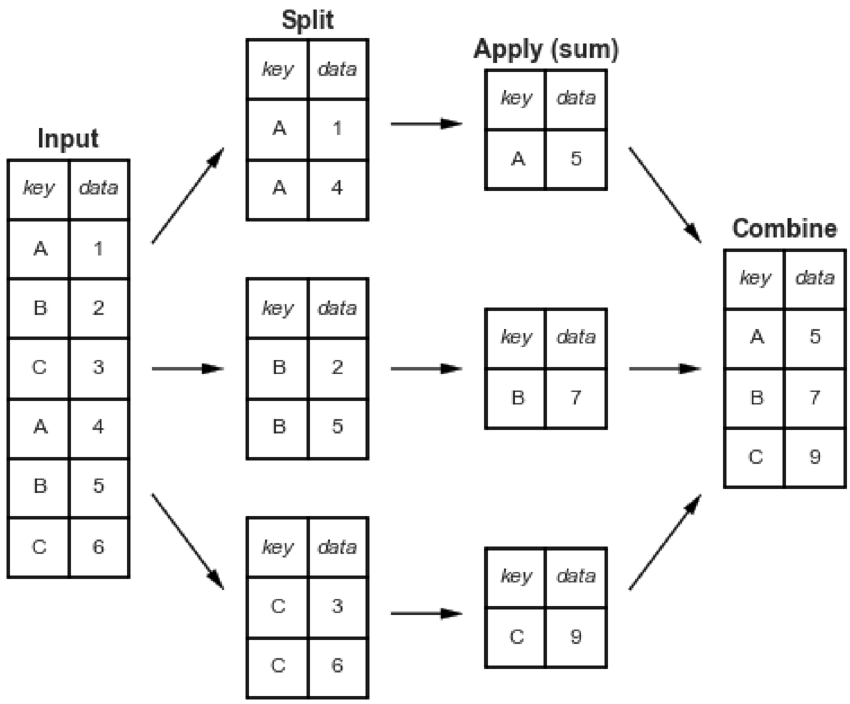
```
(498, 4)
 df.min() = orbital_period       1.3283
            mass                 0.0036
            distance             1.3500
            year              1989.0000
            dtype: float64
 df.max() = orbital_period    17337.5
            mass                 25.0
            distance            354.0
            year               2014.0
            dtype: float64
df.mean() = orbital_period     835.778671
            mass                 2.509320
            distance            52.068213
            year              2007.377510
            dtype: float64
 df.std() = orbital_period    1469.128259
            mass                 3.636274
            distance            46.596041
            year                 4.167284
            dtype: float64
```

In [145…
```
df = planets.drop(['method','number'], axis=1)
print(df.shape)
pprint('df.min()', 'df.max()', 'df.mean()', 'df.std()')
```

```
(1035, 4)
df.min() = orbital_period       0.090706
           mass                 0.003600
           distance             1.350000
           year              1989.000000
           dtype: float64
df.max() = orbital_period    730000.0
           mass                  25.0
           distance            8500.0
           year                2014.0
           dtype: float64
df.mean() = orbital_period    2002.917596
            mass                 2.638161
            distance           264.069282
            year              2009.070531
            dtype: float64
df.std() = orbital_period    26014.728304
           mass                  3.818617
           distance            733.116493
           year                  3.972567
           dtype: float64
```

The GroupBy Object

- `df.groupby()` → a *collection** of DataFrames
    - Kind os a special view of a DataFrame
- Can be indexed just like a DataFrame → a GroupBy object
- Provides easy operations of type *split-apply-combine*




```
In [146…  planets.groupby('method')
```

```
Out[146…  <pandas.core.groupby.generic.DataFrameGroupBy object at 0x7f8d9ce64c20>
```

```
In [147…  planets.groupby('method')['orbital_period']
```

```
Out[147…  <pandas.core.groupby.generic.SeriesGroupBy object at 0x7f8d9ce64320>
```

```
In [148…  planets.groupby('method')['orbital_period'].median()
```

```
Out[148…  method
          Astrometry                         631.180000
          Eclipse Timing Variations         4343.500000
          Imaging                          27500.000000
          Microlensing                      3300.000000
          Orbital Brightness Modulation        0.342887
          Pulsar Timing                       66.541900
          Pulsation Timing Variations       1170.000000
          Radial Velocity                    360.200000
          Transit                              5.714932
          Transit Timing Variations           57.011000
          Name: orbital_period, dtype: float64
```

Method not explicitly implemented by the GroupBy object are passed through and called on the groups.

```
In [149…  planets['orbital_period'].describe()
```

```
Out[149…  count       992.000000
          mean       2002.917596
          std       26014.728304
          min           0.090706
          25%           5.442540
          50%          39.979500
          75%         526.005000
          max      730000.000000
          Name: orbital_period, dtype: float64
```

```
In [150…  planets.groupby('method')['orbital_period'].describe()
```

Out[150…

method	count	mean	std	min	25%	50%	75%	ma
Astrometry	2.0	631.180000	544.217663	246.360000	438.770000	631.180000	823.590000	1016.0000
Eclipse Timing Variations	9.0	4751.644444	2499.130945	1916.250000	2900.000000	4343.500000	5767.000000	10220.0000
Imaging	12.0	118247.737500	213978.177277	4639.150000	8343.900000	27500.000000	94250.000000	730000.0000
Microlensing	7.0	3153.571429	1113.166333	1825.000000	2375.000000	3300.000000	3550.000000	5100.0000
Orbital Brightness Modulation	3.0	0.709307	0.725493	0.240104	0.291496	0.342887	0.943908	1.5449
Pulsar Timing	5.0	7343.021201	16313.265573	0.090706	25.262000	66.541900	98.211400	36525.0000
Pulsation Timing Variations	1.0	1170.000000	NaN	1170.000000	1170.000000	1170.000000	1170.000000	1170.0000
Radial Velocity	553.0	823.354680	1454.926210	0.736540	38.021000	360.200000	982.000000	17337.5000
Transit	397.0	21.102073	46.185893	0.355000	3.160630	5.714932	16.145700	331.6005
Transit Timing Variations	3.0	79.783500	71.599884	22.339500	39.675250	57.011000	108.505500	160.0000

GroupBy object is iterable

- A sequence of `(groupby_value , Series/DataFrame)` pairs

In [151…

```
for method,df in planets.groupby('method'):
    print(f'{method:30s} {df.shape=}')
```

```
Astrometry                     df.shape=(2, 6)
Eclipse Timing Variations      df.shape=(9, 6)
Imaging                        df.shape=(38, 6)
Microlensing                   df.shape=(23, 6)
Orbital Brightness Modulation  df.shape=(3, 6)
Pulsar Timing                  df.shape=(5, 6)
Pulsation Timing Variations    df.shape=(1, 6)
Radial Velocity                df.shape=(553, 6)
Transit                        df.shape=(397, 6)
Transit Timing Variations      df.shape=(4, 6)
```

Aggregate, filter, transform, apply

GroupBy objects have `aggregate()`, `filter()`, `transform()`, and `apply()` methods that efficiently implement a variety of useful operations before combining the grouped data.

In [152…

```
planets.groupby('method')[['orbital_period','distance']].aggregate(['count','min','max'])
```

Out[152...

	orbital_period			distance		
	count	min	max	count	min	max
method						
Astrometry	2	246.360000	1016.000000	2	14.98	20.77
Eclipse Timing Variations	9	1916.250000	10220.000000	4	130.72	500.00
Imaging	12	4639.150000	730000.000000	32	7.69	165.00
Microlensing	7	1825.000000	5100.000000	10	1760.00	7720.00
Orbital Brightness Modulation	3	0.240104	1.544929	2	1180.00	1180.00
Pulsar Timing	5	0.090706	36525.000000	1	1200.00	1200.00
Pulsation Timing Variations	1	1170.000000	1170.000000	0	NaN	NaN
Radial Velocity	553	0.736540	17337.500000	530	1.35	354.00
Transit	397	0.355000	331.600590	224	38.00	8500.00
Transit Timing Variations	3	22.339500	160.000000	3	339.00	2119.00

Working with Time Series

- Pandas is compatible with dates, times, and time-indexed data
- Time-based indexes can be used for time series
- Standard + date-only special indexing

Python dates and times: `datetime` and `dateutil`

In [153...

```
from datetime import datetime
date = datetime(year=2025, month=4, day=14)
date
```

Out[153...

```
datetime.datetime(2025, 4, 14, 0, 0)
```

`dateutil` module can parse dates from a variety of string formats:

In [154...

```
from dateutil import parser
date = parser.parse("14th of April, 2025")
date
```

Out[154...

```
datetime.datetime(2025, 4, 14, 0, 0)
```

NumPy's `datetime64`

In [155...

```
import numpy as np
date = np.array('2025-04-14', dtype=np.datetime64)
date
```

Out[155...

```
array('2025-04-14', dtype='datetime64[D]')
```

Vectorized operations can be applied to dates:

In [156...

```
date + np.arange(20)
```

Out[156…
```
array(['2025-04-14', '2025-04-15', '2025-04-16', '2025-04-17',
       '2025-04-18', '2025-04-19', '2025-04-20', '2025-04-21',
       '2025-04-22', '2025-04-23', '2025-04-24', '2025-04-25',
       '2025-04-26', '2025-04-27', '2025-04-28', '2025-04-29',
       '2025-04-30', '2025-05-01', '2025-05-02', '2025-05-03'],
      dtype='datetime64[D]')
```

Dates and times in Pandas

In [157…
```
date = pd.to_datetime("4th of July, 2015")
date
```

Out[157…
```
Timestamp('2015-07-04 00:00:00')
```

Vectorized operations can be applied to dates:

In [158…
```
date + pd.to_timedelta(np.arange(20), 'D')
```

Out[158…
```
DatetimeIndex(['2015-07-04', '2015-07-05', '2015-07-06', '2015-07-07',
               '2015-07-08', '2015-07-09', '2015-07-10', '2015-07-11',
               '2015-07-12', '2015-07-13', '2015-07-14', '2015-07-15',
               '2015-07-16', '2015-07-17', '2015-07-18', '2015-07-19',
               '2015-07-20', '2015-07-21', '2015-07-22', '2015-07-23'],
              dtype='datetime64[ns]', freq=None)
```

Dates and times in Pandas

`DatetimeIndex` provides a time index

In [159…
```
index = pd.DatetimeIndex(['2014-07-04', '2014-08-04',
                          '2015-07-04', '2015-08-04'])
data = pd.Series([0, 1, 2, 3], index=index)
data
```

Out[159…
```
2014-07-04    0
2014-08-04    1
2015-07-04    2
2015-08-04    3
dtype: int64
```

Standard indexing patterns:

In [160…
```
pprint("data['2014-08-04']", "data[:'2015-07-04']", "data[['2014-07-04','2015-07-04']]", alig
```

```
              data['2014-08-04'] = 1

             data[:'2015-07-04'] = 2014-07-04    0
                                   2014-08-04    1
                                   2015-07-04    2
                                   dtype: int64

data[['2014-07-04','2015-07-04']] = 2014-07-04    0
                                    2015-07-04    2
                                    dtype: int64
```

Date-only indexing patterns:

In [161…
```
pprint("data['2014']", "data[:'2015-07']", align=True, sep="\n\n")
```

```
    data['2014'] = 2014-07-04    0
                   2014-08-04    1
                   dtype: int64

data[:'2015-07'] = 2014-07-04    0
                   2014-08-04    1
                   2015-07-04    2
                   dtype: int64
```

Time Series Data Structures

- *time stamps*: `Timestamp` (np.datetime64) → `DatetimeIndex`
- *time Periods*: `Period` (np.datetime64) → `PeriodIndex`
- *time deltas or durations*: `Timedelta` (np.timedelta64) → `TimedeltaIndex`

- `pd.to_datetime()` (parser) → `Timestamp` or `DatetimeIndex`

In [162…

```
dates = pd.to_datetime([datetime(2015, 7, 3), '4th of July, 2015',
                        '2015-Jul-6', '07-07-2015', '20150708'])
pprint('dates','dates[0]', align=True)
```

```
   dates = DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-06', '2015-07-07',
                          '2015-07-08'],
                         dtype='datetime64[ns]', freq=None)
dates[0] = Timestamp('2015-07-03 00:00:00')
```

- `DatetimeIndex.to_period()` → `PeriodIndex`

In [163…

```
dates.to_period('D')
```

Out[163…

```
PeriodIndex(['2015-07-03', '2015-07-04', '2015-07-06', '2015-07-07',
             '2015-07-08'],
            dtype='period[D]')
```

In [164…

```
days = dates.to_period('D')
months = dates.to_period('M')
years = dates.to_period('Y')
pprint('dates[:2]', 'days[:2]', 'months[:2]', 'years[:2]', align=True)
```

```
 dates[:2] = DatetimeIndex(['2015-07-03', '2015-07-04'], dtype='datetime64[ns]', freq=None)
  days[:2] = PeriodIndex(['2015-07-03', '2015-07-04'], dtype='period[D]')
months[:2] = PeriodIndex(['2015-07', '2015-07'], dtype='period[M]')
 years[:2] = PeriodIndex(['2015', '2015'], dtype='period[Y-DEC]')
```

- `Timestamp - Timestamp` → `Timedelta`:

In [165…

```
dates[1]-dates[0]
```

Out[165…

```
Timedelta('1 days 00:00:00')
```

- `DatetimeIndex - Timestamp` → `TimedeltaIndex` :

In [166…

```
dates-dates[0]
```

Out[166…

```
TimedeltaIndex(['0 days', '1 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]', f
req=None)
```

- `pd.date_range()` → `DatetimeIndex`

- `pd.period_range()` → `PeriodIndex`
- `pd.timedelta_range()` → `TimedeltaIndex`

In [167…
```
pd.date_range('2015-07-03', '2015-07-10')
```

Out[167…
```
DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-05', '2015-07-06',
               '2015-07-07', '2015-07-08', '2015-07-09', '2015-07-10'],
              dtype='datetime64[ns]', freq='D')
```

In [168…
```
pd.date_range('2015-07-03', periods=8, freq='h')
```

Out[168…
```
DatetimeIndex(['2015-07-03 00:00:00', '2015-07-03 01:00:00',
               '2015-07-03 02:00:00', '2015-07-03 03:00:00',
               '2015-07-03 04:00:00', '2015-07-03 05:00:00',
               '2015-07-03 06:00:00', '2015-07-03 07:00:00'],
              dtype='datetime64[ns]', freq='h')
```

In [169…
```
pd.period_range('2015-07', periods=8, freq='M')
```

Out[169…
```
PeriodIndex(['2015-07', '2015-08', '2015-09', '2015-10', '2015-11', '2015-12',
             '2016-01', '2016-02'],
            dtype='period[M]')
```

In [170…
```
pd.timedelta_range(0, periods=10, freq='h')
```

Out[170…
```
TimedeltaIndex(['0 days 00:00:00', '0 days 01:00:00', '0 days 02:00:00',
                '0 days 03:00:00', '0 days 04:00:00', '0 days 05:00:00',
                '0 days 06:00:00', '0 days 07:00:00', '0 days 08:00:00',
                '0 days 09:00:00'],
               dtype='timedelta64[ns]', freq='h')
```

Resampling, Shifting, and Windowing

In [171…
```
#!pip install pandas-datareader
from pandas_datareader import data
#goog = data.DataReader('GOOG', start=2020, end='2024',data_source='stooq')
goog = data.DataReader('GOOG', start=2020, end='2024', data_source='stooq').sort_index()
goog.head()
```

Out[171…

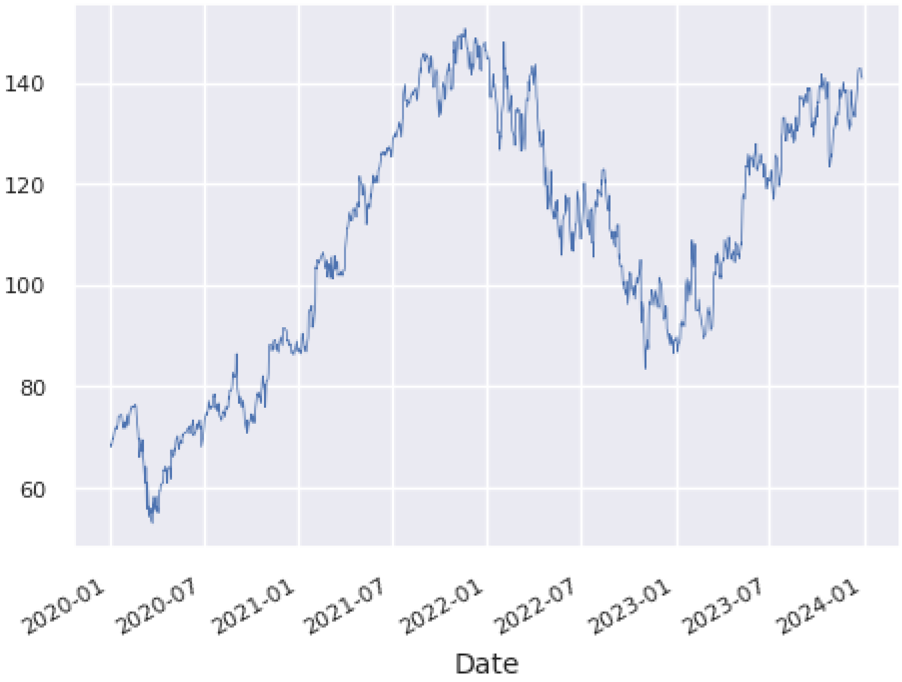
Date	Open	High	Low	Close	Volume
2020-01-02	67.0775	68.4070	67.0775	68.3685	28134620
2020-01-03	67.3930	68.6250	67.2770	68.0330	23740120
2020-01-06	67.5000	69.8250	67.5000	69.7105	34662980
2020-01-07	69.8970	70.1495	69.5190	69.6670	30233860
2020-01-08	69.6040	70.5790	69.5420	70.2160	30583540

Some visual configurations...

In [172…
```
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn
seaborn.set()
mpl.rcParams['figure.figsize'] = (5.33,4)
mpl.rcParams['axes.labelsize'] = 10  # Example: 14 points
mpl.rcParams['xtick.labelsize'] = 8  # Example: 12 points for x-axis ticks
mpl.rcParams['ytick.labelsize'] = 8  # Example: 12 points for y-axis ticks
```

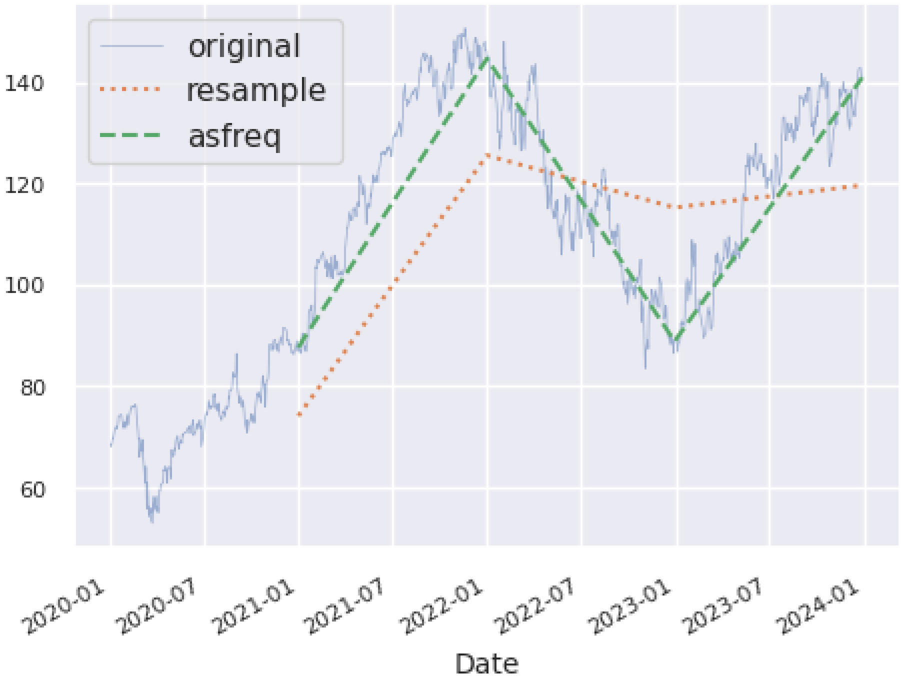
In [173…
```python
goog = goog['Close']
```

In [174…
```python
goog.plot(linewidth=0.5);
```



- `resample(freq).aggregate_func()` → data aggregation
- `asfreq(freq)` → data selection
  - ≈ `resample(freq).last()`

In [175…
```python
# 'BYE': Business Year End (last business day of year)
goog.plot(alpha=0.5, style='-', linewidth=0.5)
goog.resample('BYE').mean().plot(style=':')
goog.asfreq('BYE').plot(style='--');
plt.legend(['original', 'resample', 'asfreq'], loc='upper left');
```



Resampling can generate Null values

- `method="ffill"|"bfill"` → how values are imputed

In [176…

```
d = goog.head()
pprint("d" , "d.asfreq('D')", "d.asfreq('D',method='ffill')", align=True)
```

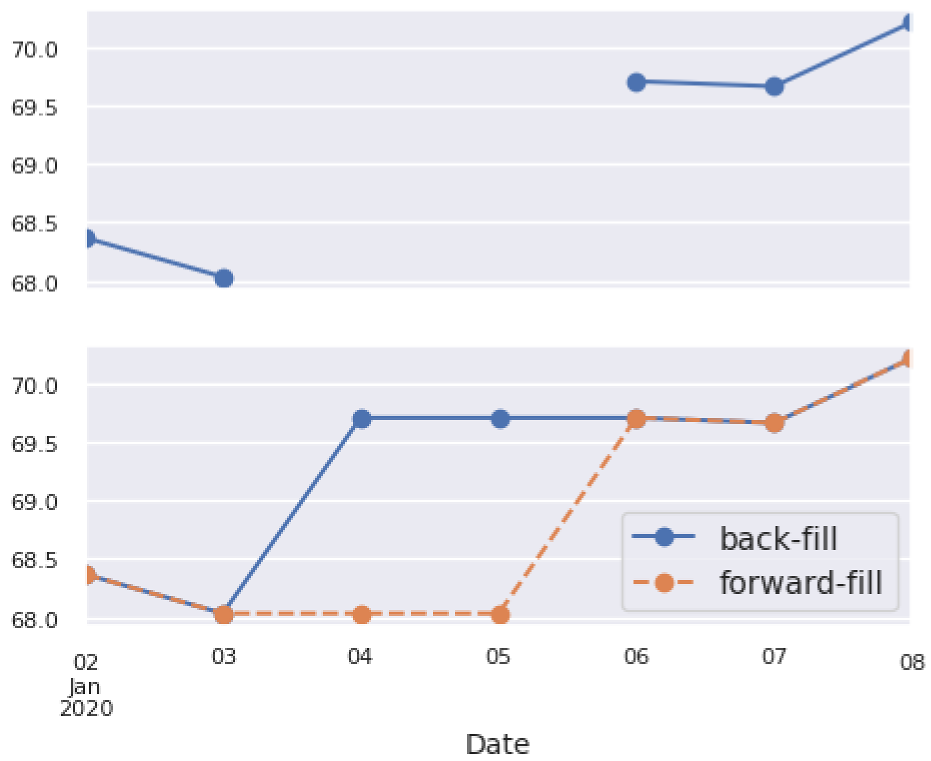
```
                         d = Date
                             2020-01-02    68.3685
                             2020-01-03    68.0330
                             2020-01-06    69.7105
                             2020-01-07    69.6670
                             2020-01-08    70.2160
                             Name: Close, dtype: float64
             d.asfreq('D') = Date
                             2020-01-02    68.3685
                             2020-01-03    68.0330
                             2020-01-04        NaN
                             2020-01-05        NaN
                             2020-01-06    69.7105
                             2020-01-07    69.6670
                             2020-01-08    70.2160
                             Freq: D, Name: Close, dtype: float64
d.asfreq('D',method='ffill') = Date
                             2020-01-02    68.3685
                             2020-01-03    68.0330
                             2020-01-04    68.0330
                             2020-01-05    68.0330
                             2020-01-06    69.7105
                             2020-01-07    69.6670
                             2020-01-08    70.2160
                             Freq: D, Name: Close, dtype: float64
```

In [177…

```
fig, ax = plt.subplots(2, sharex=True)
data = goog.head()

data.asfreq('D').plot(ax=ax[0], marker='o')

data.asfreq('D', method='bfill').plot(ax=ax[1], style='-o')
data.asfreq('D', method='ffill').plot(ax=ax[1], style='--o')
ax[1].legend(["back-fill", "forward-fill"]);
```



- `shift()` → shift the data
  - `shift(int)` → shift the data `int` positions

- `shift(int, freq)` → shift the data `int` number of `freq`

In [178…

```python
pprint("goog.head()", "goog.shift(3).head()", "goog.shift(3,'D').head()", align=True)
```

```
              goog.head() = Date
                            2020-01-02    68.3685
                            2020-01-03    68.0330
                            2020-01-06    69.7105
                            2020-01-07    69.6670
                            2020-01-08    70.2160
                            Name: Close, dtype: float64
     goog.shift(3).head() = Date
                            2020-01-02        NaN
                            2020-01-03        NaN
                            2020-01-06        NaN
                            2020-01-07    68.3685
                            2020-01-08    68.0330
                            Name: Close, dtype: float64
 goog.shift(3,'D').head() = Date
                            2020-01-05    68.3685
                            2020-01-06    68.0330
                            2020-01-09    69.7105
                            2020-01-10    69.6670
                            2020-01-11    70.2160
                            Name: Close, dtype: float64
```

Compute differences over time (frequencies):

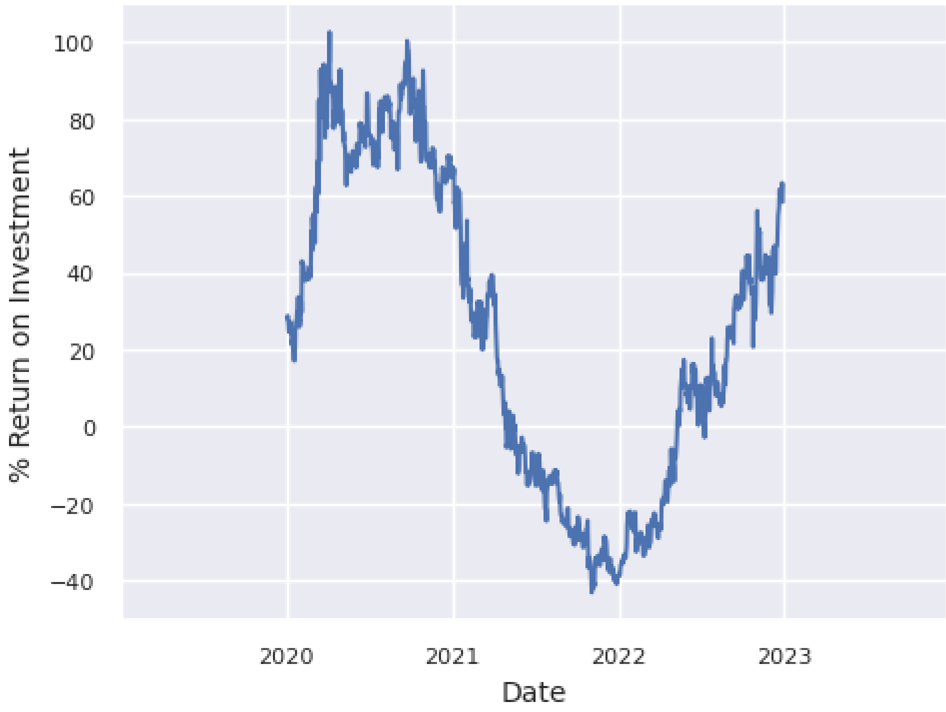
In [179…

```python
pprint("goog.head()", "goog.shift(-365,'D').head()", align=True)
```

```
                goog.head() = Date
                              2020-01-02    68.3685
                              2020-01-03    68.0330
                              2020-01-06    69.7105
                              2020-01-07    69.6670
                              2020-01-08    70.2160
                              Name: Close, dtype: float64
goog.shift(-365,'D').head() = Date
                              2019-01-02    68.3685
                              2019-01-03    68.0330
                              2019-01-06    69.7105
                              2019-01-07    69.6670
                              2019-01-08    70.2160
                              Name: Close, dtype: float64
```

In [180…

```python
data = goog.asfreq('D', method='ffill')
ROI = 100 * (data.shift(-365,'D') / data - 1)
ROI.plot()
plt.ylabel('% Return on Investment');
```



- `rolling()` → rolling window
  - aggregation functions can be applied to a rolling window

In [181…

```
r365 = goog.rolling(365).mean()
r200 = goog.rolling(200).mean()
data = pd.DataFrame({'GOOG': goog, '1year mean': r365, '200d mean': r200})
ax = data.plot(style=['-', '--', ':'])
ax.lines[0].set_alpha(0.3)
```