



**Python for Data Analysis, 3rd Edition**  
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## Chapter 5. Getting Started with pandas

pandas will be a major tool of interest throughout much of the rest of the book. It contains data structures and data manipulation tools designed to make data cleaning and analysis fast and convenient in Python. pandas is often used in tandem with numerical computing tools like NumPy and SciPy, analytical libraries like statsmodels and scikit-learn, and data visualization libraries like matplotlib. pandas adopts significant parts of NumPy's idiomatic style of array-based computing, especially array-based functions and a preference for data processing without for loops.

While pandas adopts many coding idioms from NumPy, the biggest difference is that pandas is designed for working with tabular or heterogeneous data. NumPy, by contrast, is best suited for working with homogeneously typed numerical array data.

Since becoming an open source project in 2010, pandas has matured into a quite large library that's applicable in a broad set of real-world use cases. The developer community has grown to over 2,500 distinct contributors, who've been helping build the project as they used it to solve their day-to-day data problems. The vibrant pandas developer and user communities have been a key part of its success.

### Note

Many people don't know that I haven't been actively involved in day-to-day pandas development since 2013; it has been an entirely community-managed project since then. Be sure to pass on your thanks to the core development and all the contributors for their hard work!

Throughout the rest of the book, I use the following import conventions for NumPy and pandas:

In [1]: `import numpy as np`

In [2]: `import pandas as pd`

Thus, whenever you see `pd`. in code, it's referring to pandas. You may also find it easier to import Series and DataFrame into the local namespace since they are so frequently used:

```
In [3]: from pandas import Series, DataFrame
```

## 5.1 Introduction to pandas Data Structures

To get started with pandas, you will need to get comfortable with its two workhorse data structures: *Series* and *DataFrame*. While they are not a universal solution for every problem, they provide a solid foundation for a wide variety of data tasks.

### **Series**

A Series is a one-dimensional array-like object containing a sequence of values (of similar types to NumPy types) of the same type and an associated array of data labels, called its *index*. The simplest Series is formed from only an array of data:

```
In [14]: obj = pd.Series([4, 7, -5, 3])
```

```
In [15]: obj
```

```
Out[15]:
```

```
0    4  
1    7  
2   -5  
3    3  
dtype: int64
```

The string representation of a Series displayed interactively shows the index on the left and the values on the right. Since we did not specify an index for the data, a default one consisting of the integers 0 through N - 1 (where N is the length of the data) is created. You can get the array representation and index object of the Series via its array and index attributes, respectively:

```
In [16]: obj.array
```

```
Out[16]:
```

```
<PandasArray>
```

```
[4, 7, -5, 3]
```

```
Length: 4, dtype: int64
```

```
In [17]: obj.index
```

```
Out[17]: RangeIndex(start=0, stop=4, step=1)
```

The result of the `.array` attribute is a `PandasArray` which usually wraps a NumPy array but can also contain special extension array types which will be discussed more in [Section 7.3, “Extension Data Types.”](#).

Often, you’ll want to create a Series with an index identifying each data point with a label:

```
In [18]: obj2 = pd.Series([4, 7, -5, 3], index=["d", "b", "a", "c"])
```

```
In [19]: obj2
```

```
Out[19]:
```

```
d    4  
b    7  
a   -5  
c    3  
dtype: int64
```

```
In [20]: obj2.index
```

```
Out[20]: Index(['d', 'b', 'a', 'c'], dtype='object')
```

Compared with NumPy arrays, you can use labels in the index when selecting single values or a set of values:

```
In [21]: obj2["a"]
```

```
Out[21]: -5
```

```
In [22]: obj2["d"] = 6
```

```
In [23]: obj2[["c", "a", "d"]]
```

```
Out[23]:
```

```
c 3  
a -5  
d 6  
dtype: int64
```

Here ["c", "a", "d"] is interpreted as a list of indices, even though it contains strings instead of integers.

Using NumPy functions or NumPy-like operations, such as filtering with a Boolean array, scalar multiplication, or applying math functions, will preserve the index-value link:

```
In [24]: obj2[obj2 > 0]
```

```
Out[24]:
```

```
d 6  
b 7  
c 3  
dtype: int64
```

```
In [25]: obj2 * 2
```

```
Out[25]:
```

```
d 12  
b 14  
a -10  
c 6  
dtype: int64
```

```
In [26]: import numpy as np
```

```
In [27]: np.exp(obj2)
```

```
Out[27]:
```

```
d    403.428793  
b    1096.633158  
a     0.006738  
c    20.085537  
dtype: float64
```

Another way to think about a Series is as a fixed-length, ordered dictionary, as it is a mapping of index values to data values. It can be used in many contexts where you might use a dictionary:

```
In [28]: "b" in obj2
```

```
Out[28]: True
```

```
In [29]: "e" in obj2
```

```
Out[29]: False
```

Should you have data contained in a Python dictionary, you can create a Series from it by passing the dictionary:

```
In [30]: sdata = {"Ohio": 35000, "Texas": 71000, "Oregon": 16000, "Utah": 5000}
```

```
In [31]: obj3 = pd.Series(sdata)
```

```
In [32]: obj3
```

```
Out[32]:
```

```
Ohio    35000
```

```
Texas   71000
```

```
Oregon  16000
```

```
Utah    5000
```

```
dtype: int64
```

A Series can be converted back to a dictionary with its `to_dict` method:

```
In [33]: obj3.to_dict()
```

```
Out[33]: {'Ohio': 35000, 'Texas': 71000, 'Oregon': 16000, 'Utah': 5000}
```

When you are only passing a dictionary, the index in the resulting Series will respect the order of the keys according to the dictionary's `keys` method, which depends on the key insertion order. You can override this by passing an index with the dictionary keys in the order you want them to appear in the resulting Series:

```
In [34]: states = ["California", "Ohio", "Oregon", "Texas"]
```

```
In [35]: obj4 = pd.Series(sdata, index=states)
```

```
In [36]: obj4
```

```
Out[36]:
```

```
California      NaN
```

```
Ohio        35000.0
```

```
Oregon       16000.0
```

```
Texas        71000.0
```

```
dtype: float64
```

Here, three values found in `sdata` were placed in the appropriate locations, but since no value for "California" was found, it appears as `NaN` (Not a Number), which is considered in pandas to mark missing or `NA` values. Since "Utah" was not included in `states`, it is excluded from the resulting object.

I will use the terms "missing," "NA," or "null" interchangeably to refer to missing data. The `isna` and `notna` functions in pandas should be used to detect missing data:

```
In [37]: pd.isna(obj4)
```

```
Out[37]:
```

```
California  True  
Ohio      False  
Oregon    False  
Texas     False  
dtype: bool
```

```
In [38]: pd.notna(obj4)
```

```
Out[38]:
```

```
California  False  
Ohio       True  
Oregon    True  
Texas     True  
dtype: bool
```

Series also has these as instance methods:

```
In [39]: obj4.isna()
```

```
Out[39]:
```

```
California  True  
Ohio      False  
Oregon    False  
Texas     False  
dtype: bool
```

I discuss working with missing data in more detail in [Chapter 7](#).

A useful Series feature for many applications is that it automatically aligns by index label in arithmetic operations:

```
In [40]: obj3
```

```
Out[40]:
```

```
Ohio    35000
```

```
Texas   71000
```

```
Oregon   16000
```

```
Utah    5000
```

```
dtype: int64
```

```
In [41]: obj4
```

```
Out[41]:
```

```
California    NaN
```

```
Ohio      35000.0
```

```
Oregon     16000.0
```

```
Texas      71000.0
```

```
dtype: float64
```

```
In [42]: obj3 + obj4
```

```
Out[42]:
```

```
California    NaN
```

```
Ohio      70000.0
```

```
Oregon     32000.0
```

```
Texas      142000.0
```

```
Utah      NaN
```

```
dtype: float64
```

Data alignment features will be addressed in more detail later. If you have experience with databases, you can think about this as being similar to a join operation.

Both the Series object itself and its index have a name attribute, which integrates with other areas of pandas functionality:

```
In [43]: obj4.name = "population"
```

```
In [44]: obj4.index.name = "state"
```

```
In [45]: obj4
```

```
Out[45]:
```

```
state
```

```
California    NaN
```

```
Ohio      35000.0
```

```
Oregon     16000.0
```

```
Texas      71000.0
```

```
Name: population, dtype: float64
```

A Series's index can be altered in place by assignment:

```
In [46]: obj
```

```
Out[46]:
```

```
0  4
```

```
1  7
```

```
2 -5
```

```
3  3
```

```
dtype: int64
```

```
In [47]: obj.index = ["Bob", "Steve", "Jeff", "Ryan"]
```

```
In [48]: obj
```

```
Out[48]:
```

```
Bob   4
```

```
Steve  7
```

```
Jeff  -5
```

```
Ryan  3
```

```
dtype: int64
```

## DataFrame

A DataFrame represents a rectangular table of data and contains an ordered, named collection of columns, each of which can be a different value type (numeric, string, Boolean, etc.). The DataFrame has both a row and column index; it can be thought of as a dictionary of Series all sharing the same index.

### Note

While a DataFrame is physically two-dimensional, you can use it to represent higher dimensional data in a tabular format using hierarchical indexing, a subject we will discuss in [Chapter 8](#) and an ingredient in some of the more advanced data-handling features in pandas.

There are many ways to construct a DataFrame, though one of the most common is from a dictionary of equal-length lists or NumPy arrays:

```
data = {"state": ["Ohio", "Ohio", "Ohio", "Nevada", "Nevada", "Nevada"],  
        "year": [2000, 2001, 2002, 2001, 2002, 2003],  
        "pop": [1.5, 1.7, 3.6, 2.4, 2.9, 3.2]}  
  
frame = pd.DataFrame(data)
```

The resulting DataFrame will have its index assigned automatically, as with Series, and the columns are placed according to the order of the keys in data (which depends on their insertion order in the dictionary):

```
In [50]: frame
```

```
Out[50]:
```

```
   state  year  pop  
0  Ohio  2000  1.5  
1  Ohio  2001  1.7  
2  Ohio  2002  3.6  
3 Nevada  2001  2.4  
4 Nevada  2002  2.9
```

5 Nevada 2003 3.2

### Note

If you are using the Jupyter notebook, pandas DataFrame objects will be displayed as a more browser-friendly HTML table. See [Figure 5-1](#) for an example.

	state	year	pop
0	Ohio	2000	1.5
1	Ohio	2001	1.7
2	Ohio	2002	3.6
3	Nevada	2001	2.4
4	Nevada	2002	2.9
5	Nevada	2003	3.2

Figure 5-1. How pandas DataFrame objects look in Jupyter

For large DataFrames, the head method selects only the first five rows:

In [51]: frame.head()

Out[51]:

```
state year pop
0 Ohio 2000 1.5
1 Ohio 2001 1.7
2 Ohio 2002 3.6
3 Nevada 2001 2.4
4 Nevada 2002 2.9
```

Similarly, `tail` returns the last five rows:

In [52]: `frame.tail()`

Out[52]:

```
state year pop
1 Ohio 2001 1.7
2 Ohio 2002 3.6
3 Nevada 2001 2.4
4 Nevada 2002 2.9
5 Nevada 2003 3.2
```

If you specify a sequence of columns, the DataFrame's columns will be arranged in that order:

In [53]: `pd.DataFrame(data, columns=["year", "state", "pop"])`

Out[53]:

```
year state pop
0 2000 Ohio 1.5
1 2001 Ohio 1.7
2 2002 Ohio 3.6
3 2001 Nevada 2.4
4 2002 Nevada 2.9
5 2003 Nevada 3.2
```

If you pass a column that isn't contained in the dictionary, it will appear with missing values in the result:

In [54]: `frame2 = pd.DataFrame(data, columns=["year", "state", "pop", "debt"])`

In [55]: `frame2`

Out[55]:

```
year state pop debt
0 2000 Ohio 1.5 NaN
1 2001 Ohio 1.7 NaN
2 2002 Ohio 3.6 NaN
3 2001 Nevada 2.4 NaN
4 2002 Nevada 2.9 NaN
5 2003 Nevada 3.2 NaN
```

In [56]: frame2.columns

Out[56]: Index(['year', 'state', 'pop', 'debt'], dtype='object')

A column in a DataFrame can be retrieved as a Series either by dictionary-like notation or by using the dot attribute notation:

In [57]: frame2["state"]

Out[57]:

```
0    Ohio
1    Ohio
2    Ohio
3  Nevada
4  Nevada
5  Nevada
```

Name: state, dtype: object

In [58]: frame2.year

Out[58]:

```
0  2000
1  2001
2  2002
3  2001
```

```
4 2002
```

```
5 2003
```

```
Name: year, dtype: int64
```

## Note

Attribute-like access (e.g., `frame2.year`) and tab completion of column names in IPython are provided as a convenience.

`frame2[column]` works for any column name, but `frame2.column` works only when the column name is a valid Python variable name and does not conflict with any of the method names in DataFrame. For example, if a column's name contains whitespace or symbols other than underscores, it cannot be accessed with the dot attribute method.

Note that the returned Series have the same index as the DataFrame, and their name attribute has been appropriately set.

Rows can also be retrieved by position or name with the special `iloc` and `loc` attributes (more on this later in [“Selection on DataFrame with loc and iloc”](#)):

```
In [59]: frame2.loc[1]
```

```
Out[59]:
```

```
year    2001
```

```
state   Ohio
```

```
pop     1.7
```

```
debt    NaN
```

```
Name: 1, dtype: object
```

```
In [60]: frame2.iloc[2]
```

```
Out[60]:
```

```
year    2002
```

```
state   Ohio
```

```
pop     3.6
```

```
debt    NaN
```

```
Name: 2, dtype: object
```

Columns can be modified by assignment. For example, the empty debt column could be assigned a scalar value or an array of values:

In [61]: frame2["debt"] = 16.5

In [62]: frame2

Out[62]:

```
year state pop debt
0 2000 Ohio 1.5 16.5
1 2001 Ohio 1.7 16.5
2 2002 Ohio 3.6 16.5
3 2001 Nevada 2.4 16.5
4 2002 Nevada 2.9 16.5
5 2003 Nevada 3.2 16.5
```

In [63]: frame2["debt"] = np.arange(6.)

In [64]: frame2

Out[64]:

```
year state pop debt
0 2000 Ohio 1.5 0.0
1 2001 Ohio 1.7 1.0
2 2002 Ohio 3.6 2.0
3 2001 Nevada 2.4 3.0
4 2002 Nevada 2.9 4.0
5 2003 Nevada 3.2 5.0
```

When you are assigning lists or arrays to a column, the value's length must match the length of the DataFrame. If you assign a Series, its labels will be realigned exactly to the DataFrame's index, inserting missing values in any index values not present:

```
In [65]: val = pd.Series([-1.2, -1.5, -1.7], index=["two", "four", "five"])
```

```
In [66]: frame2["debt"] = val
```

```
In [67]: frame2
```

```
Out[67]:
```

```
year state pop debt
0 2000 Ohio 1.5 NaN
1 2001 Ohio 1.7 NaN
2 2002 Ohio 3.6 NaN
3 2001 Nevada 2.4 NaN
4 2002 Nevada 2.9 NaN
5 2003 Nevada 3.2 NaN
```

Assigning a column that doesn't exist will create a new column.

The `del` keyword will delete columns like with a dictionary. As an example, I first add a new column of Boolean values where the state column equals "Ohio":

```
In [68]: frame2["eastern"] = frame2["state"] == "Ohio"
```

```
In [69]: frame2
```

```
Out[69]:
```

```
year state pop debt eastern
0 2000 Ohio 1.5 NaN True
1 2001 Ohio 1.7 NaN True
2 2002 Ohio 3.6 NaN True
3 2001 Nevada 2.4 NaN False
4 2002 Nevada 2.9 NaN False
```

```
5 2003 Nevada 3.2 NaN False
```

### Caution

New columns cannot be created with the frame2.eastern dot attribute notation.

The del method can then be used to remove this column:

```
In [70]: del frame2["eastern"]
```

```
In [71]: frame2.columns
```

```
Out[71]: Index(['year', 'state', 'pop', 'debt'], dtype='object')
```

### Caution

The column returned from indexing a DataFrame is a *view* on the underlying data, not a copy. Thus, any in-place modifications to the Series will be reflected in the DataFrame. The column can be explicitly copied with the Series's copy method.

Another common form of data is a nested dictionary of dictionaries:

```
In [72]: populations = {"Ohio": {2000: 1.5, 2001: 1.7, 2002: 3.6},  
....: "Nevada": {2001: 2.4, 2002: 2.9}}
```

If the nested dictionary is passed to the DataFrame, pandas will interpret the outer dictionary keys as the columns, and the inner keys as the row indices:

```
In [73]: frame3 = pd.DataFrame(populations)
```

```
In [74]: frame3
```

```
Out[74]:
```

```
Ohio Nevada
```

```
2000 1.5 NaN
```

```
2001 1.7 2.4
```

```
2002 3.6 2.9
```

You can transpose the DataFrame (swap rows and columns) with similar syntax to a NumPy array:

```
In [75]: frame3.T
```

```
Out[75]:
```

```
2000 2001 2002
```

```
Ohio 1.5 1.7 3.6
```

```
Nevada NaN 2.4 2.9
```

## Warning

Note that transposing discards the column data types if the columns do not all have the same data type, so transposing and then transposing back may lose the previous type information. The columns become arrays of pure Python objects in this case.

The keys in the inner dictionaries are combined to form the index in the result. This isn't true if an explicit index is specified:

```
In [76]: pd.DataFrame(populations, index=[2001, 2002, 2003])
```

```
Out[76]:
```

```
Ohio Nevada
```

```
2001 1.7 2.4
```

```
2002 3.6 2.9
```

```
2003 NaN NaN
```

Dictionaries of Series are treated in much the same way:

```
In [77]: pdata = {"Ohio": frame3["Ohio"][:-1],
```

```
....: "Nevada": frame3["Nevada"][:2]}
```

```
In [78]: pd.DataFrame(pdata)
```

```
Out[78]:
```

```
Ohio Nevada  
2000 1.5  NaN  
2001 1.7  2.4
```

For a list of many of the things you can pass to the DataFrame constructor, see [Table 5-1](#).

Type	Notes
2D ndarray	A matrix of data, passing optional row and column labels
Dictionary of arrays, lists, or tuples	Each sequence becomes a column in the DataFrame; all sequences must be the same length
NumPy structured/record array	Treated as the “dictionary of arrays” case
Dictionary of Series	Each value becomes a column; indexes from each Series are unioned together to form the result’s row index if no explicit index is passed
Dictionary of dictionaries	Each inner dictionary becomes a column; keys are unioned to form the row index as in the “dictionary of Series” case
List of dictionaries or Series	Each item becomes a row in the DataFrame; unions of dictionary keys or Series indexes become the DataFrame’s column labels

Type	Notes
List of lists or tuples	Treated as the “2D ndarray” case
Another DataFrame	The DataFrame’s indexes are used unless different ones are passed
NumPy MaskedArray	Like the “2D ndarray” case except masked values are missing in the DataFrame result

Table 5-1. Possible data inputs to the DataFrame constructor

If a DataFrame’s index and columns have their name attributes set, these will also be displayed:

```
In [79]: frame3.index.name = "year"
```

```
In [80]: frame3.columns.name = "state"
```

```
In [81]: frame3
```

```
Out[81]:
```

```
state Ohio Nevada
```

```
year
```

```
2000 1.5  NaN
```

```
2001 1.7  2.4
```

```
2002 3.6  2.9
```

Unlike Series, DataFrame does not have a name attribute. DataFrame’s `to_numpy` method returns the data contained in the DataFrame as a two-dimensional ndarray:

```
In [82]: frame3.to_numpy()
```

```
Out[82]:
```

```
array([[1.5, nan],
```

```
[1.7, 2.4],  
[3.6, 2.9]])
```

If the DataFrame's columns are different data types, the data type of the returned array will be chosen to accommodate all of the columns:

```
In [83]: frame2.to_numpy()  
Out[83]:  
array([[2000, 'Ohio', 1.5, nan],  
       [2001, 'Ohio', 1.7, nan],  
       [2002, 'Ohio', 3.6, nan],  
       [2001, 'Nevada', 2.4, nan],  
       [2002, 'Nevada', 2.9, nan],  
       [2003, 'Nevada', 3.2, nan]], dtype=object)
```

## Index Objects

pandas's Index objects are responsible for holding the axis labels (including a DataFrame's column names) and other metadata (like the axis name or names). Any array or other sequence of labels you use when constructing a Series or DataFrame is internally converted to an Index:

```
In [84]: obj = pd.Series(np.arange(3), index=["a", "b", "c"])
```

```
In [85]: index = obj.index
```

```
In [86]: index
```

```
Out[86]: Index(['a', 'b', 'c'], dtype='object')
```

```
In [87]: index[1:]
```

```
Out[87]: Index(['b', 'c'], dtype='object')
```

Index objects are immutable and thus can't be modified by the user:

```
index[1] = "d" # TypeError
```

Immutability makes it safer to share Index objects among data structures:

```
In [88]: labels = pd.Index(np.arange(3))
```

```
In [89]: labels
```

```
Out[89]: Int64Index([0, 1, 2], dtype='int64')
```

```
In [90]: obj2 = pd.Series([1.5, -2.5, 0], index=labels)
```

```
In [91]: obj2
```

```
Out[91]:
```

```
0    1.5
```

```
1   -2.5
```

```
2    0.0
```

```
dtype: float64
```

```
In [92]: obj2.index is labels
```

```
Out[92]: True
```

## Caution

Some users will not often take advantage of the capabilities provided by an Index, but because some operations will yield results containing indexed data, it's important to understand how they work.

In addition to being array-like, an Index also behaves like a fixed-size set:

```
In [93]: frame3
```

```
Out[93]:
```

```
state Ohio Nevada
```

```
year
```

```
2000 1.5  NaN
```

```
2001 1.7  2.4
```

```
2002 3.6  2.9
```

```
In [94]: frame3.columns
```

```
Out[94]: Index(['Ohio', 'Nevada'], dtype='object', name='state')
```

```
In [95]: "Ohio" in frame3.columns
```

```
Out[95]: True
```

```
In [96]: 2003 in frame3.index
```

```
Out[96]: False
```

Unlike Python sets, a pandas Index can contain duplicate labels:

```
In [97]: pd.Index(["foo", "foo", "bar", "bar"])
```

```
Out[97]: Index(['foo', 'foo', 'bar', 'bar'], dtype='object')
```

Selections with duplicate labels will select all occurrences of that label.

Each Index has a number of methods and properties for set logic, which answer other common questions about the data it contains. Some useful ones are summarized in [Table 5-2](#).

Method/Property	Description
append()	Concatenate with additional Index objects, producing a new Index
difference()	Compute set difference as an Index
intersection()	Compute set intersection
union()	Compute set union
isin()	Compute Boolean array indicating whether each value is contained in the passed collection
delete()	Compute new Index with element at Index i deleted
drop()	Compute new Index by deleting passed values
insert()	Compute new Index by inserting element at Index i
is_monotonic	Returns True if each element is greater than or equal to the previous element
is_unique	Returns True if the Index has no duplicate values
unique()	Compute the array of unique values in the Index

Table 5-2. Some Index methods and properties

## 5.2 Essential Functionality

This section will walk you through the fundamental mechanics of interacting with the data contained in a Series or DataFrame. In the chapters to come, we will delve more deeply into data analysis and manipulation topics using pandas. This book is not intended to serve as exhaustive documentation for the pandas library; instead, we'll focus on

familiarizing you with heavily used features, leaving the less common (i.e., more esoteric) things for you to learn more about by reading the online pandas documentation.

## Reindexing

An important method on pandas objects is reindex, which means to create a new object with the values rearranged to align with the new index. Consider an example:

```
In [98]: obj = pd.Series([4.5, 7.2, -5.3, 3.6], index=["d", "b", "a", "c"])
```

```
In [99]: obj
```

```
Out[99]:
```

```
d  4.5  
b  7.2  
a -5.3  
c  3.6  
dtype: float64
```

Calling reindex on this Series rearranges the data according to the new index, introducing missing values if any index values were not already present:

```
In [100]: obj2 = obj.reindex(["a", "b", "c", "d", "e"])
```

```
In [101]: obj2
```

```
Out[101]:
```

```
a -5.3  
b  7.2  
c  3.6  
d  4.5  
e  NaN  
dtype: float64
```

For ordered data like time series, you may want to do some interpolation or filling of values when reindexing. The method option allows us to do this, using a method such as ffill, which forward-fills the values:

```
In [102]: obj3 = pd.Series(["blue", "purple", "yellow"], index=[0, 2, 4])
```

```
In [103]: obj3
```

```
Out[103]:
```

```
0    blue  
2   purple  
4  yellow  
dtype: object
```

```
In [104]: obj3.reindex(np.arange(6), method="ffill")
```

```
Out[104]:
```

```
0    blue  
1    blue  
2   purple  
3   purple  
4  yellow  
5  yellow  
dtype: object
```

With DataFrame, reindex can alter the (row) index, columns, or both. When passed only a sequence, it reindexes the rows in the result:

```
In [105]: frame = pd.DataFrame(np.arange(9).reshape((3, 3)),
```

```
.....:           index=["a", "c", "d"],  
.....:           columns=["Ohio", "Texas", "California"])
```

```
In [106]: frame
```

```
Out[106]:
```

```
Ohio Texas California
a  0    1    2
c  3    4    5
d  6    7    8
```

```
In [107]: frame2 = frame.reindex(index=["a", "b", "c", "d"])
```

```
In [108]: frame2
```

```
Out[108]:
```

```
Ohio Texas California
a  0.0   1.0   2.0
b  NaN   NaN   NaN
c  3.0   4.0   5.0
d  6.0   7.0   8.0
```

The columns can be reindexed with the `columns` keyword:

```
In [109]: states = ["Texas", "Utah", "California"]
```

```
In [110]: frame.reindex(columns=states)
```

```
Out[110]:
```

```
Texas Utah California
a    1  NaN    2
c    4  NaN    5
d    7  NaN    8
```

Because "Ohio" was not in `states`, the data for that column is dropped from the result.

Another way to reindex a particular axis is to pass the new axis labels as a positional argument and then specify the axis to reindex with the axis keyword:

```
In [111]: frame.reindex(states, axis="columns")
```

```
Out[111]:
```

```
Texas Utah California  
a    1   NaN     2  
c    4   NaN     5  
d    7   NaN     8
```

See [Table 5-3](#) for more about the arguments to reindex.

Argument	Description
labels	New sequence to use as an index. Can be Index instance or any other sequence-like Python data structure. An Index will be used exactly as is without any copying.
index	Use the passed sequence as the new index labels.
columns	Use the passed sequence as the new column labels.
axis	The axis to reindex, whether "index" (rows) or "columns". The default is "index". You can alternately do reindex(index=new_labels) or reindex(columns=new_labels).
method	Interpolation (fill) method; "ffill" fills forward, while "bfill" fills backward.
fill_value	Substitute value to use when introducing missing data by reindexing. Use fill_value="missing" (the default behavior) when you want absent labels to have null values in the result.

Argument	Description
limit	When forward filling or backfilling, the maximum size gap (in number of elements) to fill.
tolerance	When forward filling or backfilling, the maximum size gap (in absolute numeric distance) to fill for inexact matches.
level	Match simple Index on level of MultiIndex; otherwise select subset of.
copy	If True, always copy underlying data even if the new index is equivalent to the old index; if False, do not copy the data when the indexes are equivalent.

Table 5-3. reindex function arguments

As we'll explore later in ["Selection on DataFrame with loc and iloc"](#), you can also reindex by using the loc operator, and many users prefer to always do it this way. This works only if all of the new index labels already exist in the DataFrame (whereas reindex will insert missing data for new labels):

```
In [112]: frame.loc[['a', 'd', 'c'], ["California", "Texas"]]
```

```
Out[112]:
```

```
California Texas
```

a	2	1
d	8	7
c	5	4

## Dropping Entries from an Axis

Dropping one or more entries from an axis is simple if you already have an index array or list without those entries, since you can use the reindex method or .loc-based indexing. As that can require a bit of munging and set logic, the drop method will return a new object with the indicated value or values deleted from an axis:

```
In [113]: obj = pd.Series(np.arange(5.), index=["a", "b", "c", "d", "e"])
```

```
In [114]: obj
```

```
Out[114]:
```

```
a 0.0
```

```
b 1.0
```

```
c 2.0
```

```
d 3.0
```

```
e 4.0
```

```
dtype: float64
```

```
In [115]: new_obj = obj.drop("c")
```

```
In [116]: new_obj
```

```
Out[116]:
```

```
a 0.0
```

```
b 1.0
```

```
d 3.0
```

```
e 4.0
```

```
dtype: float64
```

```
In [117]: obj.drop(["d", "c"])
```

```
Out[117]:
```

```
a 0.0
```

```
b 1.0
```

```
e 4.0
```

```
dtype: float64
```

With DataFrame, index values can be deleted from either axis. To illustrate this, we first create an example DataFrame:

```
In [118]: data = pd.DataFrame(np.arange(16).reshape((4, 4)),  
.....:         index=["Ohio", "Colorado", "Utah", "New York"],  
.....:         columns=["one", "two", "three", "four"])
```

In [119]: data

Out[119]:

```
one two three four  
Ohio    0  1  2  3  
Colorado 4  5  6  7  
Utah    8  9  10 11  
New York 12 13 14 15
```

Calling drop with a sequence of labels will drop values from the row labels (axis 0):

```
In [120]: data.drop(index=["Colorado", "Ohio"])
```

Out[120]:

```
one two three four  
Utah    8  9  10 11  
New York 12 13 14 15
```

To drop labels from the columns, instead use the columns keyword:

```
In [121]: data.drop(columns=["two"])
```

Out[121]:

```
one three four  
Ohio    0  2  3  
Colorado 4  6  7  
Utah    8  10 11  
New York 12 14 15
```

You can also drop values from the columns by passing axis=1 (which is like NumPy) or axis="columns":

```
In [122]: data.drop("two", axis=1)
```

```
Out[122]:
```

```
one three four  
Ohio    0   2   3  
Colorado 4   6   7  
Utah    8   10  11  
New York 12  14  15
```

```
In [123]: data.drop(["two", "four"], axis="columns")
```

```
Out[123]:
```

```
one three  
Ohio    0   2  
Colorado 4   6  
Utah    8   10  
New York 12  14
```

## Indexing, Selection, and Filtering

Series indexing (obj[...]) works analogously to NumPy array indexing, except you can use the Series's index values instead of only integers. Here are some examples of this:

```
In [124]: obj = pd.Series(np.arange(4.), index=["a", "b", "c", "d"])
```

```
In [125]: obj
```

```
Out[125]:
```

```
a  0.0  
b  1.0
```

```
c 2.0  
d 3.0  
dtype: float64
```

```
In [126]: obj["b"]  
Out[126]: 1.0
```

```
In [127]: obj[1]  
Out[127]: 1.0
```

```
In [128]: obj[2:4]  
Out[128]:  
c 2.0  
d 3.0  
dtype: float64
```

```
In [129]: obj[["b", "a", "d"]]  
Out[129]:  
b 1.0  
a 0.0  
d 3.0  
dtype: float64
```

```
In [130]: obj[[1, 3]]  
Out[130]:  
b 1.0  
d 3.0  
dtype: float64
```

```
In [131]: obj[obj < 2]  
Out[131]:
```

```
a 0.0  
b 1.0  
dtype: float64
```

While you can select data by label this way, the preferred way to select index values is with the special loc operator:

```
In [132]: obj.loc[["b", "a", "d"]]  
Out[132]:  
b 1.0  
a 0.0  
d 3.0  
dtype: float64
```

The reason to prefer loc is because of the different treatment of integers when indexing with []. Regular []-based indexing will treat integers as labels if the index contains integers, so the behavior differs depending on the data type of the index. For example:

```
In [133]: obj1 = pd.Series([1, 2, 3], index=[2, 0, 1])
```

```
In [134]: obj2 = pd.Series([1, 2, 3], index=["a", "b", "c"])
```

```
In [135]: obj1  
Out[135]:  
2 1  
0 2  
1 3  
dtype: int64
```

```
In [136]: obj2
```

```
Out[136]:
```

```
a 1  
b 2  
c 3  
dtype: int64
```

```
In [137]: obj1[[0, 1, 2]]
```

```
Out[137]:
```

```
0 2  
1 3  
2 1  
dtype: int64
```

```
In [138]: obj2[[0, 1, 2]]
```

```
Out[138]:
```

```
a 1  
b 2  
c 3  
dtype: int64
```

When using loc, the expression obj.loc[[0, 1, 2]] will fail when the index does not contain integers:

```
In [134]: obj2.loc[[0, 1]]
```

```
-----  
KeyError          Traceback (most recent call last)
```

```
/tmp/ipykernel_804589/4185657903.py in <module>  
----> 1 obj2.loc[[0, 1]]
```

```
^ LONG EXCEPTION ABBREVIATED ^
```

```
KeyError: "None of [Int64Index([0, 1], dtype="int64")] are in the [index]"
```

Since loc operator indexes exclusively with labels, there is also an iloc operator that indexes exclusively with integers to work consistently whether or not the index contains integers:

```
In [139]: obj1.iloc[[0, 1, 2]]
```

```
Out[139]:
```

```
2 1  
0 2  
1 3  
dtype: int64
```

```
In [140]: obj2.iloc[[0, 1, 2]]
```

```
Out[140]:
```

```
a 1  
b 2  
c 3  
dtype: int64
```

## Caution

You can also slice with labels, but it works differently from normal Python slicing in that the endpoint is inclusive:

```
In [141]: obj2.loc["b":"c"]
```

```
Out[141]:
```

```
b 2  
c 3  
dtype: int64
```

Assigning values using these methods modifies the corresponding section of the Series:

```
In [142]: obj2.loc["b":"c"] = 5
```

```
In [143]: obj2
```

```
Out[143]:
```

```
a 1  
b 5  
c 5  
dtype: int64
```

### Note

It can be a common newbie error to try to call loc or iloc like functions rather than “indexing into” them with square brackets. The square bracket notation is used to enable slice operations and to allow for indexing on multiple axes with DataFrame objects.

Indexing into a DataFrame retrieves one or more columns either with a single value or sequence:

```
In [144]: data = pd.DataFrame(np.arange(16).reshape((4, 4)),  
.....:     index=["Ohio", "Colorado", "Utah", "New York"],  
.....:     columns=["one", "two", "three", "four"])
```

```
In [145]: data
```

```
Out[145]:
```

```
one two three four  
Ohio    0  1  2  3  
Colorado 4  5  6  7  
Utah    8  9  10 11  
New York 12 13 14 15
```

```
In [146]: data["two"]
```

```
Out[146]:
```

```
Ohio    1
```

```
Colorado 5
```

```
Utah    9
```

```
New York 13
```

```
Name: two, dtype: int64
```

```
In [147]: data[["three", "one"]]
```

```
Out[147]:
```

```
three one
```

```
Ohio    2  0
```

```
Colorado 6  4
```

```
Utah    10 8
```

```
New York 14 12
```

Indexing like this has a few special cases. The first is slicing or selecting data with a Boolean array:

```
In [148]: data[:2]
```

```
Out[148]:
```

```
one two three four
```

```
Ohio    0  1  2  3
```

```
Colorado 4  5  6  7
```

```
In [149]: data[data["three"] > 5]
```

```
Out[149]:
```

```
one two three four
```

```
Colorado 4  5  6  7
```

```
Utah    8   9   10  11  
New York 12  13  14  15
```

The row selection syntax `data[:2]` is provided as a convenience. Passing a single element or a list to the `[]` operator selects columns.

Another use case is indexing with a Boolean DataFrame, such as one produced by a scalar comparison. Consider a DataFrame with all Boolean values produced by comparing with a scalar value:

```
In [150]: data < 5
```

```
Out[150]:
```

```
one  two three four  
Ohio  True True True True  
Colorado  True False False False  
Utah  False False False False  
New York False False False False
```

We can use this DataFrame to assign the value 0 to each location with the value True, like so:

```
In [151]: data[data < 5] = 0
```

```
In [152]: data
```

```
Out[152]:
```

```
one  two three four  
Ohio  0   0   0   0  
Colorado  0   5   6   7  
Utah    8   9   10  11  
New York 12  13  14  15
```

## Selection on DataFrame with loc and iloc

Like Series, DataFrame has special attributes loc and iloc for label-based and integer-based indexing, respectively. Since DataFrame is two-dimensional, you can select a subset of the rows and columns with NumPy-like notation using either axis labels (loc) or integers (iloc).

As a first example, let's select a single row by label:

In [153]: data

Out[153]:

```
one  two  three  four  
Ohio    0  0  0  0  
Colorado 0  5  6  7  
Utah    8  9  10 11  
New York 12 13 14 15
```

In [154]: data.loc["Colorado"]

Out[154]:

```
one    0  
two    5  
three  6  
four   7  
Name: Colorado, dtype: int64
```

The result of selecting a single row is a Series with an index that contains the DataFrame's column labels. To select multiple rows, creating a new DataFrame, pass a sequence of labels:

In [155]: data.loc[["Colorado", "New York"]]

Out[155]:

```
one  two  three  four  
Colorado 0  5  6  7
```

```
New York 12 13 14 15
```

You can combine both row and column selection in loc by separating the selections with a comma:

```
In [156]: data.loc["Colorado", ["two", "three"]]
```

```
Out[156]:
```

```
two 5
```

```
three 6
```

```
Name: Colorado, dtype: int64
```

We'll then perform some similar selections with integers using iloc:

```
In [157]: data.iloc[2]
```

```
Out[157]:
```

```
one 8
```

```
two 9
```

```
three 10
```

```
four 11
```

```
Name: Utah, dtype: int64
```

```
In [158]: data.iloc[[2, 1]]
```

```
Out[158]:
```

```
one two three four
```

```
Utah 8 9 10 11
```

```
Colorado 0 5 6 7
```

```
In [159]: data.iloc[2, [3, 0, 1]]
```

```
Out[159]:
```

```
four 11
one 8
two 9
Name: Utah, dtype: int64
```

In [160]: data.iloc[[1, 2], [3, 0, 1]]

Out[160]:

```
four one two
Colorado 7 0 5
Utah 11 8 9
```

Both indexing functions work with slices in addition to single labels or lists of labels:

In [161]: data.loc[:"Utah", "two"]

Out[161]:

```
Ohio 0
Colorado 5
Utah 9
```

Name: two, dtype: int64

In [162]: data.iloc[:, :3][data.three > 5]

Out[162]:

```
one two three
Colorado 0 5 6
Utah 8 9 10
New York 12 13 14
```

Boolean arrays can be used with loc but not iloc:

```
In [163]: data.loc[data.three >= 2]
```

```
Out[163]:
```

```
one  two  three  four  
Colorado  0  5  6  7  
Utah    8  9  10 11  
New York 12 13 14 15
```

There are many ways to select and rearrange the data contained in a pandas object. For DataFrame, [Table 5-4](#) provides a short summary of many of them. As you will see later, there are a number of additional options for working with hierarchical indexes.

Type	Notes
df[column]	Select single column or sequence of columns from the DataFrame; special case conveniences: Boolean array (filter rows), slice (slice rows), or Boolean DataFrame (set values based on some criterion)
df.loc[rows]	Select single row or subset of rows from the DataFrame by label
df.loc[:, cols]	Select single column or subset of columns by label
df.loc[rows, cols]	Select both row(s) and column(s) by label
df.iloc[rows]	Select single row or subset of rows from the DataFrame by integer position
df.iloc[:, cols]	Select single column or subset of columns by integer position
df.iloc[rows, cols]	Select both row(s) and column(s) by integer position

Type	Notes
df.at[row, col]	Select a single scalar value by row and column label
df.iat[row, col]	Select a single scalar value by row and column position (integers)
reindex method	Select either rows or columns by labels

Table 5-4. Indexing options with DataFrame

### Integer indexing pitfalls

Working with pandas objects indexed by integers can be a stumbling block for new users since they work differently from built-in Python data structures like lists and tuples. For example, you might not expect the following code to generate an error:

```
In [164]: ser = pd.Series(np.arange(3.))
```

```
In [165]: ser
```

```
Out[165]:
```

```
0 0.0
```

```
1 1.0
```

```
2 2.0
```

```
dtype: float64
```

```
In [166]: ser[-1]
```

---

```
ValueError Traceback (most recent call last)
```

```
/miniconda/envs/book-env/lib/python3.10/site-packages/pandas/core/indexes/range.p
```

```
y in get_loc(self, key, method, tolerance)
```

```
384     try:
```

```
--> 385         return self._range.index(new_key)
```

```
386     except ValueError as err:
```

```
ValueError: -1 is not in range
```

The above exception was the direct cause of the following exception:

```
KeyError          Traceback (most recent call last)

<ipython-input-166-44969a759c20> in <module>
    ----> 1 ser[-1]

/miniconda/envs/book-env/lib/python3.10/site-packages/pandas/core/series.py in __
getitem__(self, key)

  956
  957      elif key_is_scalar:
--> 958          return self._get_value(key)

  959
  960      if is_hashable(key):

/miniconda/envs/book-env/lib/python3.10/site-packages/pandas/core/series.py in _g
et_value(self, label, takeable)

 1067
 1068      # Similar to Index.get_value, but we do not fall back to position
al
-> 1069      loc = self.index.get_loc(label)
 1070      return self.index._get_values_for_loc(self, loc, label)

 1071

/miniconda/envs/book-env/lib/python3.10/site-packages/pandas/core/indexes/range.p
y in get_loc(self, key, method, tolerance)

 385          return self._range.index(new_key)
 386      except ValueError as err:
--> 387          raise KeyError(key) from err
 388      self._check_indexing_error(key)
 389      raise KeyError(key)

KeyError: -1
```

In this case, pandas could “fall back” on integer indexing, but it is difficult to do this in general without introducing subtle bugs into the user code. Here we have an index containing 0, 1, and 2, but pandas does not want to guess what the user wants (label-based indexing or position-based):

```
In [167]: ser
```

```
Out[167]:
```

```
0 0.0
```

```
1 1.0
```

```
2 2.0
```

```
dtype: float64
```

On the other hand, with a noninteger index, there is no such ambiguity:

```
In [168]: ser2 = pd.Series(np.arange(3.), index=["a", "b", "c"])
```

```
In [169]: ser2[-1]
```

```
Out[169]: 2.0
```

If you have an axis index containing integers, data selection will always be label oriented. As I said above, if you use loc (for labels) or iloc (for integers) you will get exactly what you want:

```
In [170]: ser.iloc[-1]
```

```
Out[170]: 2.0
```

On the other hand, slicing with integers is always integer oriented:

```
In [171]: ser[:2]
```

```
Out[171]:
```

```
0 0.0
```

```
1 1.0  
dtype: float64
```

As a result of these pitfalls, it is best to always prefer indexing with loc and iloc to avoid ambiguity.

### Pitfalls with chained indexing

In the previous section we looked at how you can do flexible selections on a DataFrame using loc and iloc. These indexing attributes can also be used to modify DataFrame objects in place, but doing so requires some care.

For example, in the example DataFrame above, we can assign to a column or row by label or integer position:

```
In [172]: data.loc[:, "one"] = 1
```

```
In [173]: data
```

```
Out[173]:
```

```
    one two three four  
Ohio    1  0  0  0  
Colorado 1  5  6  7  
Utah    1  9  10 11  
New York 1 13 14 15
```

```
In [174]: data.iloc[2] = 5
```

```
In [175]: data
```

```
Out[175]:
```

```
    one two three four  
Ohio    1  0  0  0  
Colorado 1  5  6  7  
Utah    5  5  5  5  
New York 1 13 14 15
```

```
In [176]: data.loc[data["four"] > 5] = 3
```

```
In [177]: data
```

```
Out[177]:
```

	one	two	three	four
Ohio	1	0	0	0
Colorado	3	3	3	3
Utah	5	5	5	5
New York	3	3	3	3

A common gotcha for new pandas users is to chain selections when assigning, like this:

```
In [177]: data.loc[data.three == 5]["three"] = 6
```

```
<ipython-input-11-0ed1cf2155d5>:1: SettingWithCopyWarning:
```

A value is trying to be set on a copy of a slice from a DataFrame.

Try using `.loc[row_indexer,col_indexer] = value` instead

Depending on the data contents, this may print a special `SettingWithCopyWarning`, which warns you that you are trying to modify a temporary value (the nonempty result of `data.loc[data.three == 5]`) instead of the original DataFrame data, which might be what you were intending. Here, data was unmodified:

```
In [179]: data
```

```
Out[179]:
```

	one	two	three	four
Ohio	1	0	0	0
Colorado	3	3	3	3
Utah	5	5	5	5
New York	3	3	3	3

In these scenarios, the fix is to rewrite the chained assignment to use a single loc operation:

```
In [180]: data.loc[data.three == 5, "three"] = 6
```

```
In [181]: data
```

```
Out[181]:
```

```
one two three four  
Ohio    1  0  0  0  
Colorado 3  3  3  3  
Utah    5  5  6  5  
New York 3  3  3  3
```

A good rule of thumb is to avoid chained indexing when doing assignments. There are other cases where pandas will generate SettingWithCopyWarning that have to do with chained indexing. I refer you to this topic in the online pandas documentation.

### Arithmetic and Data Alignment

pandas can make it much simpler to work with objects that have different indexes. For example, when you add objects, if any index pairs are not the same, the respective index in the result will be the union of the index pairs. Let's look at an example:

```
In [182]: s1 = pd.Series([7.3, -2.5, 3.4, 1.5], index=["a", "c", "d", "e"])
```

```
In [183]: s2 = pd.Series([-2.1, 3.6, -1.5, 4, 3.1],
```

```
.....:      index=["a", "c", "e", "f", "g"])
```

```
In [184]: s1
```

```
Out[184]:
```

```
a  7.3
```

```
c -2.5
```

```
d 3.4  
e 1.5  
dtype: float64
```

In [185]: s2

Out[185]:

```
a -2.1  
c 3.6  
e -1.5  
f 4.0  
g 3.1  
dtype: float64
```

Adding these yields:

```
In [186]: s1 + s2  
Out[186]:  
a 5.2  
c 1.1  
d NaN  
e 0.0  
f NaN  
g NaN  
dtype: float64
```

The internal data alignment introduces missing values in the label locations that don't overlap. Missing values will then propagate in further arithmetic computations.

In the case of DataFrame, alignment is performed on both rows and columns:

```
In [187]: df1 = pd.DataFrame(np.arange(9.).reshape((3, 3)), columns=list("bcd"),
.....:           index=["Ohio", "Texas", "Colorado"])
```

```
In [188]: df2 = pd.DataFrame(np.arange(12.).reshape((4, 3)), columns=list("bde"),
.....:           index=["Utah", "Ohio", "Texas", "Oregon"])
```

```
In [189]: df1
```

```
Out[189]:
```

```
   b   c   d
Ohio  0.0  1.0  2.0
Texas  3.0  4.0  5.0
Colorado  6.0  7.0  8.0
```

```
In [190]: df2
```

```
Out[190]:
```

```
   b   d   e
Utah  0.0  1.0  2.0
Ohio  3.0  4.0  5.0
Texas  6.0  7.0  8.0
Oregon  9.0  10.0  11.0
```

Adding these returns a DataFrame with index and columns that are the unions of the ones in each DataFrame:

```
In [191]: df1 + df2
```

```
Out[191]:
```

```
   b   c   d   e
Colorado  NaN  NaN  NaN  NaN
Ohio      3.0  NaN  6.0  NaN
Oregon    NaN  NaN  NaN  NaN
```

```
Texas 9.0 NaN 12.0 NaN
```

```
Utah  NaN NaN  NaN NaN
```

Since the "c" and "e" columns are not found in both DataFrame objects, they appear as missing in the result. The same holds for the rows with labels that are not common to both objects.

If you add DataFrame objects with no column or row labels in common, the result will contain all nulls:

```
In [192]: df1 = pd.DataFrame({"A": [1, 2]})
```

```
In [193]: df2 = pd.DataFrame({"B": [3, 4]})
```

```
In [194]: df1
```

```
Out[194]:
```

```
A
```

```
0 1
```

```
1 2
```

```
In [195]: df2
```

```
Out[195]:
```

```
B
```

```
0 3
```

```
1 4
```

```
In [196]: df1 + df2
```

```
Out[196]:
```

```
A B
```

```
0 NaN NaN
```

```
1 NaN NaN
```

## Arithmetic methods with fill values

In arithmetic operations between differently indexed objects, you might want to fill with a special value, like 0, when an axis label is found in one object but not the other. Here is an example where we set a particular value to NA (null) by assigning np.nan to it:

```
In [197]: df1 = pd.DataFrame(np.arange(12.).reshape((3, 4)),  
.....:           columns=list("abcd"))
```

```
In [198]: df2 = pd.DataFrame(np.arange(20.).reshape((4, 5)),  
.....:           columns=list("abcde"))
```

```
In [199]: df2.loc[1, "b"] = np.nan
```

```
In [200]: df1
```

```
Out[200]:
```

```
   a   b   c   d  
0  0.0  1.0  2.0  3.0  
1  4.0  5.0  6.0  7.0  
2  8.0  9.0 10.0 11.0
```

```
In [201]: df2
```

```
Out[201]:
```

```
   a   b   c   d   e  
0  0.0  1.0  2.0  3.0  4.0  
1  5.0  NaN  7.0  8.0  9.0  
2 10.0 11.0 12.0 13.0 14.0  
3 15.0 16.0 17.0 18.0 19.0
```

Adding these results in missing values in the locations that don't overlap:

```
In [202]: df1 + df2
```

```
Out[202]:
```

```
   a   b   c   d   e  
0  0.0  2.0  4.0  6.0  NaN  
1  9.0  NaN  13.0 15.0  NaN  
2 18.0 20.0 22.0 24.0  NaN  
3  NaN  NaN  NaN  NaN  NaN
```

Using the add method on df1, I pass df2 and an argument to fill\_value, which substitutes the passed value for any missing values in the operation:

```
In [203]: df1.add(df2, fill_value=0)
```

```
Out[203]:
```

```
   a   b   c   d   e  
0  0.0  2.0  4.0  6.0  4.0  
1  9.0  5.0  13.0 15.0  9.0  
2 18.0 20.0 22.0 24.0 14.0  
3 15.0 16.0 17.0 18.0 19.0
```

See [Table 5-5](#) for a listing of Series and DataFrame methods for arithmetic. Each has a counterpart, starting with the letter r, that has arguments reversed. So these two statements are equivalent:

```
In [204]: 1 / df1
```

```
Out[204]:
```

```
   a      b      c      d  
0  inf  1.000000  0.500000  0.333333  
1  0.250  0.200000  0.166667  0.142857  
2  0.125  0.111111  0.100000  0.090909
```

```
In [205]: df1.rdiv(1)
```

```
Out[205]:
```

```
      a      b      c      d  
0  inf  1.000000  0.500000  0.333333  
1  0.250  0.200000  0.166667  0.142857  
2  0.125  0.111111  0.100000  0.090909
```

Relatedly, when reindexing a Series or DataFrame, you can also specify a different fill value:

```
In [206]: df1.reindex(columns=df2.columns, fill_value=0)
```

```
Out[206]:
```

```
      a      b      c      d      e  
0  0.0  1.0  2.0  3.0  0  
1  4.0  5.0  6.0  7.0  0  
2  8.0  9.0  10.0 11.0  0
```

Method	Description
add, radd	Methods for addition (+)
sub, rsub	Methods for subtraction (-)
div, rdiv	Methods for division (/)
floordiv, rfloordiv	Methods for floor division (//)

Method	Description
mul, rmul	Methods for multiplication (*)
pow, rpow	Methods for exponentiation (**)

Table 5-5. Flexible arithmetic methods

### Operations between DataFrame and Series

As with NumPy arrays of different dimensions, arithmetic between DataFrame and Series is also defined. First, as a motivating example, consider the difference between a two-dimensional array and one of its rows:

```
In [207]: arr = np.arange(12.).reshape((3, 4))
```

```
In [208]: arr
```

```
Out[208]:
```

```
array([[ 0.,  1.,  2.,  3.],
       [ 4.,  5.,  6.,  7.],
       [ 8.,  9., 10., 11.]])
```

```
In [209]: arr[0]
```

```
Out[209]: array([0., 1., 2., 3.])
```

```
In [210]: arr - arr[0]
```

```
Out[210]:
```

```
array([[0., 0., 0., 0.],
       [4., 4., 4., 4.],
       [8., 8., 8., 8.]])
```

When we subtract arr[0] from arr, the subtraction is performed once for each row. This is referred to as *broadcasting* and is explained in more detail as it relates to general NumPy arrays in [Appendix A](#). Operations between a DataFrame and a Series are similar:

```
In [211]: frame = pd.DataFrame(np.arange(12.).reshape((4, 3)),
```

```
.....:         columns=list("bde"),
.....:         index=["Utah", "Ohio", "Texas", "Oregon"])
```

```
In [212]: series = frame.iloc[0]
```

```
In [213]: frame
```

```
Out[213]:
```

```
    b   d   e
Utah  0.0  1.0  2.0
Ohio   3.0  4.0  5.0
Texas  6.0  7.0  8.0
Oregon 9.0 10.0 11.0
```

```
In [214]: series
```

```
Out[214]:
```

```
    b   0.0
    d   1.0
    e   2.0
```

```
Name: Utah, dtype: float64
```

By default, arithmetic between DataFrame and Series matches the index of the Series on the columns of the DataFrame, broadcasting down the rows:

```
In [215]: frame - series
```

```
Out[215]:
```

```
    b   d   e
Utah  0.0  0.0  0.0
```

```
Ohio 3.0 3.0 3.0  
Texas 6.0 6.0 6.0  
Oregon 9.0 9.0 9.0
```

If an index value is not found in either the DataFrame's columns or the Series's index, the objects will be reindexed to form the union:

```
In [216]: series2 = pd.Series(np.arange(3), index=["b", "e", "f"])
```

```
In [217]: series2
```

```
Out[217]:
```

```
b 0  
e 1  
f 2  
dtype: int64
```

```
In [218]: frame + series2
```

```
Out[218]:
```

```
      b   d   e   f  
Utah  0.0 NaN  3.0 NaN  
Ohio  3.0 NaN  6.0 NaN  
Texas 6.0 NaN  9.0 NaN  
Oregon 9.0 NaN 12.0 NaN
```

If you want to instead broadcast over the columns, matching on the rows, you have to use one of the arithmetic methods and specify to match over the index. For example:

```
In [219]: series3 = frame["d"]
```

```
In [220]: frame
```

```
Out[220]:
```

```
      b   d   e  
Utah  0.0  1.0  2.0  
Ohio   3.0  4.0  5.0  
Texas  6.0  7.0  8.0  
Oregon 9.0 10.0 11.0
```

```
In [221]: series3
```

```
Out[221]:
```

```
Utah    1.0  
Ohio    4.0  
Texas   7.0  
Oregon  10.0
```

```
Name: d, dtype: float64
```

```
In [222]: frame.sub(series3, axis="index")
```

```
Out[222]:
```

```
      b   d   e  
Utah -1.0  0.0  1.0  
Ohio  -1.0  0.0  1.0  
Texas -1.0  0.0  1.0  
Oregon -1.0 0.0 1.0
```

The axis that you pass is the *axis to match on*. In this case we mean to match on the DataFrame's row index (axis="index") and broadcast across the columns.

## Function Application and Mapping

NumPy ufuncs (element-wise array methods) also work with pandas objects:

```
In [223]: frame = pd.DataFrame(np.random.standard_normal((4, 3)),
```

```
.....:           columns=list("bde"),
```

```
.....: index=["Utah", "Ohio", "Texas", "Oregon"])
```

In [224]: frame

Out[224]:

```
      b      d      e  
Utah -0.204708 0.478943 -0.519439  
Ohio -0.555730 1.965781 1.393406  
Texas 0.092908 0.281746 0.769023  
Oregon 1.246435 1.007189 -1.296221
```

In [225]: np.abs(frame)

Out[225]:

```
      b      d      e  
Utah 0.204708 0.478943 0.519439  
Ohio 0.555730 1.965781 1.393406  
Texas 0.092908 0.281746 0.769023  
Oregon 1.246435 1.007189 1.296221
```

Another frequent operation is applying a function on one-dimensional arrays to each column or row. DataFrame's apply method does exactly this:

In [226]: def f1(x):

```
.....: return x.max() - x.min()
```

In [227]: frame.apply(f1)

Out[227]:

```
b 1.802165  
d 1.684034  
e 2.689627  
dtype: float64
```

Here the function f, which computes the difference between the maximum and minimum of a Series, is invoked once on each column in frame. The result is a Series having the columns of frame as its index.

If you pass axis="columns" to apply, the function will be invoked once per row instead. A helpful way to think about this is as “apply across the columns”:

In [228]: frame.apply(f1, axis="columns")

Out[228]:

Utah 0.998382

Ohio 2.521511

Texas 0.676115

Oregon 2.542656

dtype: float64

Many of the most common array statistics (like sum and mean) are DataFrame methods, so using apply is not necessary.

The function passed to apply need not return a scalar value; it can also return a Series with multiple values:

In [229]: def f2(x):

```
.....:     return pd.Series([x.min(), x.max()], index=["min", "max"])
```

In [230]: frame.apply(f2)

Out[230]:

b d e

min -0.555730 0.281746 -1.296221

max 1.246435 1.965781 1.393406

Element-wise Python functions can be used, too. Suppose you wanted to compute a formatted string from each floating-point value in frame. You can do this with applymap:

In [231]: def my\_format(x):

```
.....:     return f"{x:.2f}"
```

In [232]: frame.applymap(my\_format)

Out[232]:

```
b    d    e  
Utah -0.20 0.48 -0.52  
Ohio -0.56 1.97 1.39  
Texas 0.09 0.28 0.77  
Oregon 1.25 1.01 -1.30
```

The reason for the name applymap is that Series has a map method for applying an element-wise function:

In [233]: frame["e"].map(my\_format)

Out[233]:

```
Utah -0.52  
Ohio 1.39  
Texas 0.77  
Oregon -1.30
```

Name: e, dtype: object

## Sorting and Ranking

Sorting a dataset by some criterion is another important built-in operation. To sort lexicographically by row or column label, use the sort\_index method, which returns a new, sorted object:

In [234]: obj = pd.Series(np.arange(4), index=["d", "a", "b", "c"])

```
In [235]: obj
```

```
Out[235]:
```

```
d 0
```

```
a 1
```

```
b 2
```

```
c 3
```

```
dtype: int64
```

```
In [236]: obj.sort_index()
```

```
Out[236]:
```

```
a 1
```

```
b 2
```

```
c 3
```

```
d 0
```

```
dtype: int64
```

With a DataFrame, you can sort by index on either axis:

```
In [237]: frame = pd.DataFrame(np.arange(8).reshape((2, 4)),
```

```
.....:           index=["three", "one"],
```

```
.....:           columns=["d", "a", "b", "c"])
```

```
In [238]: frame
```

```
Out[238]:
```

```
   d a b c
```

```
three 0 1 2 3
```

```
one  4 5 6 7
```

```
In [239]: frame.sort_index()
```

Out[239]:

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

In [240]: frame.sort\_index(axis="columns")

Out[240]:

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

The data is sorted in ascending order by default but can be sorted in descending order, too:

In [241]: frame.sort\_index(axis="columns", ascending=False)

Out[241]:

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

To sort a Series by its values, use its sort\_values method:

In [242]: obj = pd.Series([4, 7, -3, 2])

In [243]: obj.sort\_values()

Out[243]:

```
2 -3  
3 2  
0 4
```

```
1 7  
dtype: int64
```

Any missing values are sorted to the end of the Series by default:

```
In [244]: obj = pd.Series([4, np.nan, 7, np.nan, -3, 2])
```

```
In [245]: obj.sort_values()
```

Out[245]:

```
4 -3.0  
5 2.0  
0 4.0  
2 7.0  
1 NaN  
3 NaN  
dtype: float64
```

Missing values can be sorted to the start instead by using the na\_position option:

```
In [246]: obj.sort_values(na_position="first")
```

Out[246]:

```
1 NaN  
3 NaN  
4 -3.0  
5 2.0  
0 4.0  
2 7.0  
dtype: float64
```

When sorting a DataFrame, you can use the data in one or more columns as the sort keys. To do so, pass one or more column names to `sort_values`:

```
In [247]: frame = pd.DataFrame({"b": [4, 7, -3, 2], "a": [0, 1, 0, 1]})
```

```
In [248]: frame
```

```
Out[248]:
```

b	a
0	4
1	7
2	-3
3	2
4	1

```
In [249]: frame.sort_values("b")
```

```
Out[249]:
```

b	a
2	-3
3	2
0	4
1	7

To sort by multiple columns, pass a list of names:

```
In [250]: frame.sort_values(["a", "b"])
```

```
Out[250]:
```

b	a
2	-3
0	4
3	2
1	7

```
1 7 1
```

*Ranking* assigns ranks from one through the number of valid data points in an array, starting from the lowest value. The rank methods for Series and DataFrame are the place to look; by default, rank breaks ties by assigning each group the mean rank:

```
In [251]: obj = pd.Series([7, -5, 7, 4, 2, 0, 4])
```

```
In [252]: obj.rank()
```

```
Out[252]:
```

```
0    6.5  
1    1.0  
2    6.5  
3    4.5  
4    3.0  
5    2.0  
6    4.5  
dtype: float64
```

Ranks can also be assigned according to the order in which they're observed in the data:

```
In [253]: obj.rank(method="first")
```

```
Out[253]:
```

```
0    6.0  
1    1.0  
2    7.0  
3    4.0  
4    3.0  
5    2.0  
6    5.0  
dtype: float64
```

```
dtype: float64
```

Here, instead of using the average rank 6.5 for the entries 0 and 2, they instead have been set to 6 and 7 because label 0 precedes label 2 in the data.

You can rank in descending order, too:

```
In [254]: obj.rank(ascending=False)
```

```
Out[254]:
```

```
0 1.5
```

```
1 7.0
```

```
2 1.5
```

```
3 3.5
```

```
4 5.0
```

```
5 6.0
```

```
6 3.5
```

```
dtype: float64
```

See [Table 5-6](#) for a list of tie-breaking methods available.

DataFrame can compute ranks over the rows or the columns:

```
In [255]: frame = pd.DataFrame({"b": [4.3, 7, -3, 2], "a": [0, 1, 0, 1],
```

```
.....: "c": [-2, 5, 8, -2.5]})
```

```
In [256]: frame
```

```
Out[256]:
```

```
   b  a  c
```

```
0 4.3 0 -2.0
```

```
1 7.0 1 5.0
```

```
2 -3.0 0 8.0
```

3 2.0 1 -2.5

In [257]: frame.rank(axis="columns")

Out[257]:

	b	a	c
0	3.0	2.0	1.0
1	3.0	1.0	2.0
2	1.0	2.0	3.0
3	3.0	2.0	1.0

<b>Method</b>	<b>Description</b>
---------------	--------------------

"average"	Default: assign the average rank to each entry in the equal group
-----------	---

"min"	Use the minimum rank for the whole group
-------	--

"max"	Use the maximum rank for the whole group
-------	--

"first"	Assign ranks in the order the values appear in the data
---------	---

"dense"	Like method="min", but ranks always increase by 1 between groups rather than the number of equal elements in a group
---------	--

Table 5-6. Tie-breaking methods with rank

### Axis Indexes with Duplicate Labels

Up until now almost all of the examples we have looked at have unique axis labels (index values). While many pandas functions (like reindex) require that the labels be unique, it's not mandatory. Let's consider a small Series with duplicate indices:

In [258]: obj = pd.Series(np.arange(5), index=["a", "a", "b", "b", "c"])

```
In [259]: obj
```

```
Out[259]:
```

```
a 0  
a 1  
b 2  
b 3  
c 4  
dtype: int64
```

The `is_unique` property of the index can tell you whether or not its labels are unique:

```
In [260]: obj.index.is_unique
```

```
Out[260]: False
```

Data selection is one of the main things that behaves differently with duplicates. Indexing a label with multiple entries returns a Series, while single entries return a scalar value:

```
In [261]: obj["a"]
```

```
Out[261]:
```

```
a 0  
a 1  
dtype: int64
```

```
In [262]: obj["c"]
```

```
Out[262]: 4
```

This can make your code more complicated, as the output type from indexing can vary based on whether or not a label is repeated.

The same logic extends to indexing rows (or columns) in a DataFrame:

```
In [263]: df = pd.DataFrame(np.random.standard_normal((5, 3)),  
.....:           index=["a", "a", "b", "b", "c"])
```

```
In [264]: df
```

```
Out[264]:
```

```
0    1    2  
a  0.274992 0.228913 1.352917  
a  0.886429 -2.001637 -0.371843  
b  1.669025 -0.438570 -0.539741  
b  0.476985 3.248944 -1.021228  
c -0.577087 0.124121 0.302614
```

```
In [265]: df.loc["b"]
```

```
Out[265]:
```

```
0    1    2  
b  1.669025 -0.438570 -0.539741  
b  0.476985 3.248944 -1.021228
```

```
In [266]: df.loc["c"]
```

```
Out[266]:
```

```
0 -0.577087  
1  0.124121  
2  0.302614
```

```
Name: c, dtype: float64
```

### 5.3 Summarizing and Computing Descriptive Statistics

pandas objects are equipped with a set of common mathematical and statistical methods. Most of these fall into the category of *reductions* or *summary statistics*, methods that extract a single value (like the sum or mean) from a Series, or a

Series of values from the rows or columns of a DataFrame. Compared with the similar methods found on NumPy arrays, they have built-in handling for missing data. Consider a small DataFrame:

```
In [267]: df = pd.DataFrame([[1.4, np.nan], [7.1, -4.5],
```

```
.....:     [np.nan, np.nan], [0.75, -1.3]],  
.....:     index=["a", "b", "c", "d"],  
.....:     columns=["one", "two"])
```

```
In [268]: df
```

```
Out[268]:
```

```
   one  two  
a  1.40  NaN  
b  7.10 -4.5  
c  NaN  NaN  
d  0.75 -1.3
```

Calling DataFrame's sum method returns a Series containing column sums:

```
In [269]: df.sum()
```

```
Out[269]:
```

```
one    9.25  
two   -5.80  
dtype: float64
```

Passing axis="columns" or axis=1 sums across the columns instead:

```
In [270]: df.sum(axis="columns")
```

```
Out[270]:
```

```
a  1.40  
b  2.60
```

```
c  0.00  
d -0.55  
dtype: float64
```

When an entire row or column contains all NA values, the sum is 0, whereas if any value is not NA, then the result is NA. This can be disabled with the skipna option, in which case any NA value in a row or column names the corresponding result NA:

```
In [271]: df.sum(axis="index", skipna=False)
```

```
Out[271]:
```

```
one  NaN  
two  NaN  
dtype: float64
```

```
In [272]: df.sum(axis="columns", skipna=False)
```

```
Out[272]:
```

```
a  NaN  
b  2.60  
c  NaN  
d -0.55  
dtype: float64
```

Some aggregations, like mean, require at least one non-NA value to yield a value result, so here we have:

```
In [273]: df.mean(axis="columns")
```

```
Out[273]:
```

```
a  1.400  
b  1.300  
c  NaN
```

```
d -0.275  
dtype: float64
```

See [Table 5-7](#) for a list of common options for each reduction method.

Method	Description
axis	Axis to reduce over; “index” for DataFrame’s rows and “columns” for columns
skipna	Exclude missing values; True by default
level	Reduce grouped by level if the axis is hierarchically indexed (MultiIndex)

Table 5-7. Options for reduction methods

Some methods, like idxmin and idxmax, return indirect statistics, like the index value where the minimum or maximum values are attained:

```
In [274]: df.idxmax()
```

```
Out[274]:
```

```
one b
```

```
two d
```

```
dtype: object
```

Other methods are *accumulations*:

```
In [275]: df.cumsum()
```

```
Out[275]:
```

```
one two
```

```
a 1.40 NaN
```

```
b 8.50 -4.5  
c NaN NaN  
d 9.25 -5.8
```

Some methods are neither reductions nor accumulations. `describe` is one such example, producing multiple summary statistics in one shot:

```
In [276]: df.describe()  
Out[276]:  
  
      one    two  
count 3.000000 2.000000  
mean 3.083333 -2.900000  
std  3.493685 2.262742  
min  0.750000 -4.500000  
25%  1.075000 -3.700000  
50%  1.400000 -2.900000  
75%  4.250000 -2.100000  
max  7.100000 -1.300000
```

On nonnumeric data, `describe` produces alternative summary statistics:

```
In [277]: obj = pd.Series(["a", "a", "b", "c"] * 4)
```

```
In [278]: obj.describe()
```

```
Out[278]:  
  
      count 16  
      unique 3  
      top    a  
      freq   8
```

`dtype: object`

See [Table 5-8](#) for a full list of summary statistics and related methods.

Method	Description
<code>count</code>	Number of non-NA values
<code>describe</code>	Compute set of summary statistics
<code>min, max</code>	Compute minimum and maximum values
<code>argmin,</code> <code>argmax</code>	Compute index locations (integers) at which minimum or maximum value is obtained, respectively; not available on DataFrame objects
<code>idxmin,</code> <code>idxmax</code>	Compute index labels at which minimum or maximum value is obtained, respectively
<code>quantile</code>	Compute sample quantile ranging from 0 to 1 (default: 0.5)
<code>sum</code>	Sum of values
<code>mean</code>	Mean of values
<code>median</code>	Arithmetic median (50% quantile) of values
<code>mad</code>	Mean absolute deviation from mean value
<code>prod</code>	Product of all values

<b>Method</b>	<b>Description</b>
var	Sample variance of values
std	Sample standard deviation of values
skew	Sample skewness (third moment) of values
kurt	Sample kurtosis (fourth moment) of values
cumsum	Cumulative sum of values
cummin, cummax	Cumulative minimum or maximum of values, respectively
cumprod	Cumulative product of values
diff	Compute first arithmetic difference (useful for time series)
pct_change	Compute percent changes

Table 5-8. Descriptive and summary statistics

### Correlation and Covariance

Some summary statistics, like correlation and covariance, are computed from pairs of arguments. Let's consider some `DataFrames` of stock prices and volumes originally obtained from Yahoo! Finance and available in binary Python pickle files you can find in the accompanying datasets for the book:

```
In [279]: price = pd.read_pickle("examples/yahoo_price.pkl")
```

```
In [280]: volume = pd.read_pickle("examples/yahoo_volume.pkl")
```

I now compute percent changes of the prices, a time series operation that will be explored further in [Chapter 11](#):

```
In [281]: returns = price.pct_change()
```

```
In [282]: returns.tail()
```

```
Out[282]:
```

```
AAPL    GOOG    IBM    MSFT  
Date  
2016-10-17 -0.000680 0.001837 0.002072 -0.003483  
2016-10-18 -0.000681 0.019616 -0.026168 0.007690  
2016-10-19 -0.002979 0.007846 0.003583 -0.002255  
2016-10-20 -0.000512 -0.005652 0.001719 -0.004867  
2016-10-21 -0.003930 0.003011 -0.012474 0.042096
```

The corr method of Series computes the correlation of the overlapping, non-NA, aligned-by-index values in two Series. Relatedly, cov computes the covariance:

```
In [283]: returns["MSFT"].corr(returns["IBM"])
```

```
Out[283]: 0.49976361144151144
```

```
In [284]: returns["MSFT"].cov(returns["IBM"])
```

```
Out[284]: 8.870655479703546e-05
```

Since MSFT is a valid Python variable name, we can also select these columns using more concise syntax:

```
In [285]: returns["MSFT"].corr(returns["IBM"])
```

```
Out[285]: 0.49976361144151144
```

DataFrame's corr and cov methods, on the other hand, return a full correlation or covariance matrix as a DataFrame, respectively:

In [286]: `returns.corr()`

Out[286]:

```
AAPL  GOOG  IBM  MSFT  
AAPL 1.000000 0.407919 0.386817 0.389695  
GOOG 0.407919 1.000000 0.405099 0.465919  
IBM 0.386817 0.405099 1.000000 0.499764  
MSFT 0.389695 0.465919 0.499764 1.000000
```

In [287]: `returns.cov()`

Out[287]:

```
AAPL  GOOG  IBM  MSFT  
AAPL 0.000277 0.000107 0.000078 0.000095  
GOOG 0.000107 0.000251 0.000078 0.000108  
IBM 0.000078 0.000078 0.000146 0.000089  
MSFT 0.000095 0.000108 0.000089 0.000215
```

Using DataFrame's corrwith method, you can compute pair-wise correlations between a DataFrame's columns or rows with another Series or DataFrame. Passing a Series returns a Series with the correlation value computed for each column:

In [288]: `returns.corrwith(returns["IBM"])`

Out[288]:

```
AAPL  0.386817  
GOOG  0.405099  
IBM  1.000000  
MSFT  0.499764  
dtype: float64
```

Passing a DataFrame computes the correlations of matching column names. Here, I compute correlations of percent changes with volume:

```
In [289]: returns.corrwith(volume)
```

```
Out[289]:
```

```
AAPL -0.075565
```

```
GOOG -0.007067
```

```
IBM -0.204849
```

```
MSFT -0.092950
```

```
dtype: float64
```

Passing axis="columns" does things row-by-row instead. In all cases, the data points are aligned by label before the correlation is computed.

### **Unique Values, Value Counts, and Membership**

Another class of related methods extracts information about the values contained in a one-dimensional Series. To illustrate these, consider this example:

```
In [290]: obj = pd.Series(["c", "a", "d", "a", "a", "b", "b", "c", "c"])
```

The first function is unique, which gives you an array of the unique values in a Series:

```
In [291]: uniques = obj.unique()
```

```
In [292]: uniques
```

```
Out[292]: array(['c', 'a', 'd', 'b'], dtype=object)
```

The unique values are not necessarily returned in the order in which they first appear, and not in sorted order, but they could be sorted after the fact if needed (`uniques.sort()`). Relatedly, `value_counts` computes a Series containing value frequencies:

```
In [293]: obj.value_counts()
```

```
Out[293]:
```

```
c 3  
a 3  
b 2  
d 1  
dtype: int64
```

The Series is sorted by value in descending order as a convenience. `value_counts` is also available as a top-level pandas method that can be used with NumPy arrays or other Python sequences:

```
In [294]: pd.value_counts(obj.to_numpy(), sort=False)
```

```
Out[294]:
```

```
c 3  
a 3  
d 1  
b 2  
dtype: int64
```

`isin` performs a vectorized set membership check and can be useful in filtering a dataset down to a subset of values in a Series or column in a DataFrame:

```
In [295]: obj
```

```
Out[295]:
```

```
0 c  
1 a  
2 d
```

```
3  a  
4  a  
5  b  
6  b  
7  c  
8  c  
dtype: object
```

```
In [296]: mask = obj.isin(["b", "c"])
```

```
In [297]: mask
```

```
Out[297]:
```

```
0  True  
1  False  
2  False  
3  False  
4  False  
5  True  
6  True  
7  True  
8  True  
dtype: bool
```

```
In [298]: obj[mask]
```

```
Out[298]:
```

```
0  c  
5  b  
6  b  
7  c  
8  c  
dtype: object
```

Related to `isin` is the `Index.get_indexer` method, which gives you an index array from an array of possibly nondistinct values into another array of distinct values:

```
In [299]: to_match = pd.Series(["c", "a", "b", "b", "c", "a"])
```

```
In [300]: unique_vals = pd.Series(["c", "b", "a"])
```

```
In [301]: indices = pd.Index(unique_vals).get_indexer(to_match)
```

```
In [302]: indices
```

```
Out[302]: array([0, 2, 1, 1, 0, 2])
```

See [Table 5-9](#) for a reference on these methods.

Method	Description
<code>isin</code>	Compute a Boolean array indicating whether each Series or DataFrame value is contained in the passed sequence of values
<code>get_indexer</code>	Compute integer indices for each value in an array into another array of distinct values; helpful for data alignment and join-type operations
<code>unique</code>	Compute an array of unique values in a Series, returned in the order observed
<code>value_counts</code>	Return a Series containing unique values as its index and frequencies as its values, ordered count in descending order

Method	Description
--------	-------------

Table 5-9. Unique, value counts, and set membership methods

In some cases, you may want to compute a histogram on multiple related columns in a DataFrame. Here's an example:

In [303]: `data = pd.DataFrame({"Qu1": [1, 3, 4, 3, 4],`

.....: "Qu2": [2, 3, 1, 2, 3],

.....: "Qu3": [1, 5, 2, 4, 4]})

In [304]: `data`

Out[304]:

Qu1 Qu2 Qu3

0 1 2 1

1 3 3 5

2 4 1 2

3 3 2 4

4 4 3 4

We can compute the value counts for a single column, like so:

In [305]: `data["Qu1"].value_counts().sort_index()`

Out[305]:

1 1

3 2

4 2

Name: Qu1, dtype: int64

To compute this for all columns, pass pandas.value\_counts to the DataFrame's apply method:

```
In [306]: result = data.apply(pd.value_counts).fillna(0)
```

```
In [307]: result
```

```
Out[307]:
```

	Qu1	Qu2	Qu3
1	1.0	1.0	1.0
2	0.0	2.0	1.0
3	2.0	2.0	0.0
4	2.0	0.0	2.0
5	0.0	0.0	1.0

Here, the row labels in the result are the distinct values occurring in all of the columns. The values are the respective counts of these values in each column.

There is also a DataFrame.value\_counts method, but it computes counts considering each row of the DataFrame as a tuple to determine the number of occurrences of each distinct row:

```
In [308]: data = pd.DataFrame({"a": [1, 1, 1, 2, 2], "b": [0, 0, 1, 0, 0]})
```

```
In [309]: data
```

```
Out[309]:
```

	a	b
0	1	0
1	1	0
2	1	1
3	2	0
4	2	0

```
In [310]: data.value_counts()
```

```
Out[310]:
```

```
a b  
1 0 2  
2 0 2  
1 1 1  
dtype: int64
```

In this case, the result has an index representing the distinct rows as a hierarchical index, a topic we will explore in greater detail in [Chapter 8](#).

#### 5.4 Conclusion

In the next chapter, we will discuss tools for reading (or *loading*) and writing datasets with pandas. After that, we will dig deeper into data cleaning, wrangling, analysis, and visualization tools using pandas.