```
In[8]: # slicing by implicit integer index
       data[0:2]
```

```
Out[8]: a    0.25
        b    0.50
        dtype: float64
```

```
In[9]: # masking
       data[(data > 0.3) & (data < 0.8)]
```

```
Out[9]: b    0.50
        c    0.75
        dtype: float64
```

```
In[10]: # fancy indexing
        data[['a', 'e']]
```

```
Out[10]: a    0.25
         e    1.25
         dtype: float64
```

Among these, slicing may be the source of the most confusion. Notice that when you are slicing with an explicit index (i.e., `data['a':'c']`), the final index is *included* in the slice, while when you're slicing with an implicit index (i.e., `data[0:2]`), the final index is *excluded* from the slice.

Indexers: loc, iloc, and ix

These slicing and indexing conventions can be a source of confusion. For example, if your `Series` has an explicit integer index, an indexing operation such as `data[1]` will use the explicit indices, while a slicing operation like `data[1:3]` will use the implicit Python-style index.

```
In[11]: data = pd.Series(['a', 'b', 'c'], index=[1, 3, 5])
        data
```

```
Out[11]: 1    a
         3    b
         5    c
         dtype: object
```

```
In[12]: # explicit index when indexing
        data[1]
```

```
Out[12]: 'a'
```

```
In[13]: # implicit index when slicing
        data[1:3]
```

```
Out[13]: 3    b
         5    c
         dtype: object
```

Because of this potential confusion in the case of integer indexes, Pandas provides some special *indexer* attributes that explicitly expose certain indexing schemes. These are not functional methods, but attributes that expose a particular slicing interface to the data in the `Series`.

First, the `loc` attribute allows indexing and slicing that always references the explicit index:

```
In[14]: data.loc[1]
```

```
Out[14]: 'a'
```

```
In[15]: data.loc[1:3]
```

```
Out[15]: 1    a
         3    b
         dtype: object
```

The `iloc` attribute allows indexing and slicing that always references the implicit Python-style index:

```
In[16]: data.iloc[1]
```

```
Out[16]: 'b'
```

```
In[17]: data.iloc[1:3]
```

```
Out[17]: 3    b
         5    c
         dtype: object
```

A third indexing attribute, `ix`, is a hybrid of the two, and for `Series` objects is equivalent to standard `[]`-based indexing. The purpose of the `ix` indexer will become more apparent in the context of `DataFrame` objects, which we will discuss in a moment.

One guiding principle of Python code is that "explicit is better than implicit." The explicit nature of `loc` and `iloc` make them very useful in maintaining clean and readable code; especially in the case of integer indexes, I recommend using these both to make code easier to read and understand, and to prevent subtle bugs due to the mixed indexing/slicing convention.

Data Selection in DataFrame

Recall that a `DataFrame` acts in many ways like a two-dimensional or structured array, and in other ways like a dictionary of `Series` structures sharing the same index. These analogies can be helpful to keep in mind as we explore data selection within this structure.

DataFrame as a dictionary

The first analogy we will consider is the `DataFrame` as a dictionary of related `Series` objects. Let's return to our example of areas and populations of states:

```
In[18]: area = pd.Series({'California': 423967, 'Texas': 695662,
                          'New York': 141297, 'Florida': 170312,
                          'Illinois': 149995})
        pop = pd.Series({'California': 38332521, 'Texas': 26448193,
                         'New York': 19651127, 'Florida': 19552860,
                         'Illinois': 12882135})
        data = pd.DataFrame({'area':area, 'pop':pop})
        data
```

```
Out[18]:             area      pop
         California  423967  38332521
         Florida     170312  19552860
         Illinois    149995  12882135
         New York    141297  19651127
         Texas       695662  26448193
```

The individual `Series` that make up the columns of the `DataFrame` can be accessed via dictionary-style indexing of the column name:

```
In[19]: data['area']
```

```
Out[19]: California    423967
         Florida       170312
         Illinois      149995
         New York      141297
         Texas         695662
         Name: area, dtype: int64
```

Equivalently, we can use attribute-style access with column names that are strings:

```
In[20]: data.area
```

```
Out[20]: California    423967
         Florida       170312
         Illinois      149995
         New York      141297
         Texas         695662
         Name: area, dtype: int64
```

This attribute-style column access actually accesses the exact same object as the dictionary-style access:

```
In[21]: data.area is data['area']
```

```
Out[21]: True
```

Though this is a useful shorthand, keep in mind that it does not work for all cases! For example, if the column names are not strings, or if the column names conflict with methods of the `DataFrame`, this attribute-style access is not possible. For example, the `DataFrame` has a `pop()` method, so `data.pop` will point to this rather than the `"pop"` column:

```
In[22]: data.pop is data['pop']
```

```
Out[22]: False
```

In particular, you should avoid the temptation to try column assignment via attribute (i.e., use `data['pop'] = z` rather than `data.pop = z`).

Like with the `Series` objects discussed earlier, this dictionary-style syntax can also be used to modify the object, in this case to add a new column:

```
In[23]: data['density'] = data['pop'] / data['area']
        data

Out[23]:             area    pop       density
         California  423967  38332521   90.413926
         Florida     170312  19552860  114.806121
         Illinois    149995  12882135   85.883763
         New York    141297  19651127  139.076746
         Texas       695662  26448193   38.018740
```

This shows a preview of the straightforward syntax of element-by-element arithmetic between `Series` objects; we'll dig into this further in "Operating on Data in Pandas" on page 115.

DataFrame as two-dimensional array

As mentioned previously, we can also view the `DataFrame` as an enhanced two-dimensional array. We can examine the raw underlying data array using the `values` attribute:

```
In[24]: data.values

Out[24]: array([[  4.23967000e+05,   3.83325210e+07,   9.04139261e+01],
                [  1.70312000e+05,   1.95528600e+07,   1.14806121e+02],
                [  1.49995000e+05,   1.28821350e+07,   8.58837628e+01],
                [  1.41297000e+05,   1.96511270e+07,   1.39076746e+02],
                [  6.95662000e+05,   2.64481930e+07,   3.80187404e+01]])
```

With this picture in mind, we can do many familiar array-like observations on the `DataFrame` itself. For example, we can transpose the full `DataFrame` to swap rows and columns:

```
In[25]: data.T

Out[25]:
         California    Florida       Illinois      New York      Texas
area     4.239670e+05  1.703120e+05  1.499950e+05  1.412970e+05  6.956620e+05
pop      3.833252e+07  1.955286e+07  1.288214e+07  1.965113e+07  2.644819e+07
density  9.041393e+01  1.148061e+02  8.588376e+01  1.390767e+02  3.801874e+01
```

When it comes to indexing of `DataFrame` objects, however, it is clear that the dictionary-style indexing of columns precludes our ability to simply treat it as a NumPy array. In particular, passing a single index to an array accesses a row:

```
In[26]: data.values[0]

Out[26]: array([  4.23967000e+05,   3.83325210e+07,   9.04139261e+01])
```

and passing a single "index" to a `DataFrame` accesses a column:

```
In[27]: data['area']

Out[27]: California    423967
         Florida       170312
         Illinois      149995
         New York      141297
         Texas         695662
         Name: area, dtype: int64
```

Thus for array-style indexing, we need another convention. Here Pandas again uses the `loc`, `iloc`, and `ix` indexers mentioned earlier. Using the `iloc` indexer, we can index the underlying array as if it is a simple NumPy array (using the implicit Python-style index), but the `DataFrame` index and column labels are maintained in the result:

```
In[28]: data.iloc[:3, :2]

Out[28]:             area    pop
         California  423967  38332521
         Florida     170312  19552860
         Illinois    149995  12882135

In[29]: data.loc[:'Illinois', :'pop']

Out[29]:             area    pop
         California  423967  38332521
         Florida     170312  19552860
         Illinois    149995  12882135
```

The `ix` indexer allows a hybrid of these two approaches:

```
In[30]: data.ix[:3, :'pop']

Out[30]:             area    pop
         California  423967  38332521
         Florida     170312  19552860
         Illinois    149995  12882135
```

Keep in mind that for integer indices, the `ix` indexer is subject to the same potential sources of confusion as discussed for integer-indexed `Series` objects.

Any of the familiar NumPy-style data access patterns can be used within these indexers. For example, in the `loc` indexer we can combine masking and fancy indexing as in the following:

```
In[31]: data.loc[data.density > 100, ['pop', 'density']]

Out[31]:           pop       density
         Florida   19552860  114.806121
         New York  19651127  139.076746
```

Any of these indexing conventions may also be used to set or modify values; this is done in the standard way that you might be accustomed to from working with NumPy:

```
In[32]: data.iloc[0, 2] = 90
        data

Out[32]:             area    pop       density
         California  423967  38332521   90.000000
         Florida     170312  19552860  114.806121
         Illinois    149995  12882135   85.883763
         New York    141297  19651127  139.076746
         Texas       695662  26448193   38.018740
```

To build up your fluency in Pandas data manipulation, I suggest spending some time with a simple `DataFrame` and exploring the types of indexing, slicing, masking, and fancy indexing that are allowed by these various indexing approaches.

Additional indexing conventions

There are a couple extra indexing conventions that might seem at odds with the preceding discussion, but nevertheless can be very useful in practice. First, while *indexing* refers to columns, *slicing* refers to rows:

```
In[33]: data['Florida':'Illinois']

Out[33]:           area    pop       density
         Florida   170312  19552860  114.806121
         Illinois  149995  12882135   85.883763
```

Such slices can also refer to rows by number rather than by index:

```
In[34]: data[1:3]

Out[34]:           area    pop       density
         Florida   170312  19552860  114.806121
         Illinois  149995  12882135   85.883763
```

Similarly, direct masking operations are also interpreted row-wise rather than column-wise:

```
In[35]: data[data.density > 100]

Out[35]:           area    pop       density
         Florida   170312  19552860  114.806121
         New York  141297  19651127  139.076746
```

These two conventions are syntactically similar to those on a NumPy array, and while these may not precisely fit the mold of the Pandas conventions, they are nevertheless quite useful in practice.

Operating on Data in Pandas

One of the essential pieces of NumPy is the ability to perform quick element-wise operations, both with basic arithmetic (addition, subtraction, multiplication, etc.) and with more sophisticated operations (trigonometric functions, exponential and logarithmic functions, etc.). Pandas inherits much of this functionality from NumPy, and the ufuncs that we introduced in "Computation on NumPy Arrays: Universal Functions" on page 50 are key to this.

Pandas includes a couple useful twists, however: for unary operations like negation and trigonometric functions, these ufuncs will *preserve index and column labels* in the output, and for binary operations such as addition and multiplication, Pandas will automatically *align indices* when passing the objects to the ufunc. This means that keeping the context of data and combining data from different sources—both potentially error-prone tasks with raw NumPy arrays—become essentially foolproof ones with Pandas. We will additionally see that there are well-defined operations between one-dimensional `Series` structures and two-dimensional `DataFrame` structures.

Ufuncs: Index Preservation

Because Pandas is designed to work with NumPy, any NumPy ufunc will work on Pandas `Series` and `DataFrame` objects. Let's start by defining a simple `Series` and `DataFrame` on which to demonstrate this:

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

In[2]: rng = np.random.RandomState(42)
       ser = pd.Series(rng.randint(0, 10, 4))
       ser

Out[2]: 0    6
        1    3
        2    7
        3    4
        dtype: int64

In[3]: df = pd.DataFrame(rng.randint(0, 10, (3, 4)),
                         columns=['A', 'B', 'C', 'D'])
       df

Out[3]:    A  B  C  D
        0  6  9  2  6
        1  7  4  3  7
        2  7  2  5  4
```

If we apply a NumPy ufunc on either of these objects, the result will be another Pandas object *with the indices preserved:*

```
In[4]: np.exp(ser)
```

```
Out[4]: 0     403.428793
        1      20.085537
        2    1096.633158
        3      54.598150
        dtype: float64
```

Or, for a slightly more complex calculation:

```
In[5]: np.sin(df * np.pi / 4)
```

```
Out[5]:           A             B         C             D
        0 -1.000000  7.071068e-01  1.000000 -1.000000e+00
        1 -0.707107  1.224647e-16  0.707107 -7.071068e-01
        2 -0.707107  1.000000e+00 -0.707107  1.224647e-16
```

Any of the ufuncs discussed in "Computation on NumPy Arrays: Universal Functions" on page 50 can be used in a similar manner.

UFuncs: Index Alignment

For binary operations on two `Series` or `DataFrame` objects, Pandas will align indices in the process of performing the operation. This is very convenient when you are working with incomplete data, as we'll see in some of the examples that follow.

Index alignment in Series

As an example, suppose we are combining two different data sources, and find only the top three US states by *area* and the top three US states by *population*:

```
In[6]: area = pd.Series({'Alaska': 1723337, 'Texas': 695662,
                         'California': 423967}, name='area')
       population = pd.Series({'California': 38332521, 'Texas': 26448193,
                               'New York': 19651127}, name='population')
```

Let's see what happens when we divide these to compute the population density:

```
In[7]: population / area
```

```
Out[7]: Alaska              NaN
        California    90.413926
        New York            NaN
        Texas         38.018740
        dtype: float64
```

The resulting array contains the *union* of indices of the two input arrays, which we could determine using standard Python set arithmetic on these indices:

```
In[8]: area.index | population.index
```

```
Out[8]: Index(['Alaska', 'California', 'New York', 'Texas'], dtype='object')
```

Any item for which one or the other does not have an entry is marked with `NaN`, or "Not a Number," which is how Pandas marks missing data (see further discussion of missing data in "Handling Missing Data" on page 119). This index matching is implemented this way for any of Python's built-in arithmetic expressions; any missing values are filled in with NaN by default:

```
In[9]: A = pd.Series([2, 4, 6], index=[0, 1, 2])
       B = pd.Series([1, 3, 5], index=[1, 2, 3])
       A + B
```

```
Out[9]: 0    NaN
        1    5.0
        2    9.0
        3    NaN
        dtype: float64
```

If using NaN values is not the desired behavior, we can modify the fill value using appropriate object methods in place of the operators. For example, calling `A.add(B)` is equivalent to calling `A + B`, but allows optional explicit specification of the fill value for any elements in `A` or `B` that might be missing:

```
In[10]: A.add(B, fill_value=0)
```

```
Out[10]: 0    2.0
         1    5.0
         2    9.0
         3    5.0
         dtype: float64
```

Index alignment in DataFrame

A similar type of alignment takes place for *both* columns and indices when you are performing operations on `DataFrame`s:

```
In[11]: A = pd.DataFrame(rng.randint(0, 20, (2, 2)),
                         columns=list('AB'))
        A
```

```
Out[11]:    A   B
         0  1  11
         1  5   1
```

```
In[12]: B = pd.DataFrame(rng.randint(0, 10, (3, 3)),
                         columns=list('BAC'))
        B
```

```
Out[12]:    B  A  C
         0  4  0  9
         1  5  8  0
         2  9  2  6
```

```
In[13]: A + B
```

```
Out[13]:       A     B   C
         0   1.0  15.0 NaN
         1  13.0   6.0 NaN
         2   NaN   NaN NaN
```

Notice that indices are aligned correctly irrespective of their order in the two objects, and indices in the result are sorted. As was the case with `Series`, we can use the associated object's arithmetic method and pass any desired `fill_value` to be used in place of missing entries. Here we'll fill with the mean of all values in `A` (which we compute by first stacking the rows of `A`):

```
In[14]: fill = A.stack().mean()
        A.add(B, fill_value=fill)
```

```
Out[14]:       A     B     C
         0   1.0  15.0  13.5
         1  13.0   6.0   4.5
         2   6.5  13.5  10.5
```

Table 3-1 lists Python operators and their equivalent Pandas object methods.

Table 3-1. Mapping between Python operators and Pandas methods

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

Ufuncs: Operations Between DataFrame and Series

When you are performing operations between a `DataFrame` and a `Series`, the index and column alignment is similarly maintained. Operations between a `DataFrame` and a `Series` are similar to operations between a two-dimensional and one-dimensional NumPy array. Consider one common operation, where we find the difference of a two-dimensional array and one of its rows:

```
In[15]: A = rng.randint(10, size=(3, 4))
        A
```

```
Out[15]: array([[3, 8, 2, 4],
                [2, 6, 4, 8],
                [6, 1, 3, 8]])
```

```
In[16]: A - A[0]
```

```
Out[16]: array([[ 0,  0,  0,  0],
                [-1, -2,  2,  4],
                [ 3, -7,  1,  4]])
```

According to NumPy's broadcasting rules (see "Computation on Arrays: Broadcasting" on page 63), subtraction between a two-dimensional array and one of its rows is applied row-wise.

In Pandas, the convention similarly operates row-wise by default:

```
In[17]: df = pd.DataFrame(A, columns=list('QRST'))
        df - df.iloc[0]
```

```
Out[17]:    Q  R  S  T
         0  0  0  0  0
         1 -1 -2  2  4
         2  3 -7  1  4
```

If you would instead like to operate column-wise, you can use the object methods mentioned earlier, while specifying the `axis` keyword:

```
In[18]: df.subtract(df['R'], axis=0)
```

```
Out[18]:    Q  R  S  T
         0 -5  0 -6 -4
         1 -4  0 -2  2
         2  5  0  2  7
```

Note that these `DataFrame`/`Series` operations, like the operations discussed before, will automatically align indices between the two elements:

```
In[19]: halfrow = df.iloc[0, ::2]
        halfrow
```

```
Out[19]: Q    3
         S    2
         Name: 0, dtype: int64
```

```
In[20]: df - halfrow
```

```
Out[20]:      Q   R    S   T
         0  0.0 NaN  0.0 NaN
         1 -1.0 NaN  2.0 NaN
         2  3.0 NaN  1.0 NaN
```

This preservation and alignment of indices and columns means that operations on data in Pandas will always maintain the data context, which prevents the types of silly errors that might come up when you are working with heterogeneous and/or misaligned data in raw NumPy arrays.

Handling Missing Data

The difference between data found in many tutorials and data in the real world is that real-world data is rarely clean and homogeneous. In particular, many interesting datasets will have some amount of data missing. To make matters even more complicated, different data sources may indicate missing data in different ways.

In this section, we will discuss some general considerations for missing data, discuss how Pandas chooses to represent it, and demonstrate some built-in Pandas tools for handling missing data in Python. Here and throughout the book, we'll refer to missing data in general as *null*, *NaN*, or *NA* values.

Trade-Offs in Missing Data Conventions

A number of schemes have been developed to indicate the presence of missing data in a table or `DataFrame`. Generally, they revolve around one of two strategies: using a *mask* that globally indicates missing values, or choosing a *sentinel value* that indicates a missing entry.

In the masking approach, the mask might be an entirely separate Boolean array, or it may involve appropriation of one bit in the data representation to locally indicate the null status of a value.

In the sentinel approach, the sentinel value could be some data-specific convention, such as indicating a missing integer value with –9999 or some rare bit pattern, or it could be a more global convention, such as indicating a missing floating-point value with NaN (Not a Number), a special value which is part of the IEEE floating-point specification.

None of these approaches is without trade-offs: use of a separate mask array requires allocation of an additional Boolean array, which adds overhead in both storage and computation. A sentinel value reduces the range of valid values that can be represented, and may require extra (often non-optimized) logic in CPU and GPU arithmetic. Common special values like NaN are not available for all data types.

As in most cases where no universally optimal choice exists, different languages and systems use different conventions. For example, the R language uses reserved bit patterns within each data type as sentinel values indicating missing data, while the SciDB system uses an extra byte attached to every cell to indicate a NA state.

Missing Data in Pandas

The way in which Pandas handles missing values is constrained by its reliance on the NumPy package, which does not have a built-in notion of NA values for non-floating-point data types.

Pandas could have followed R's lead in specifying bit patterns for each individual data type to indicate nullness, but this approach turns out to be rather unwieldy. While R contains four basic data types, NumPy supports *far* more than this: for example, while R has a single integer type, NumPy supports *fourteen* basic integer types once you account for available precisions, signedness, and endianness of the encoding. Reserving a specific bit pattern in all available NumPy types would lead to an unwieldy amount of overhead in special-casing various operations for various types, likely even requiring a new fork of the NumPy package. Further, for the smaller data types (such as 8-bit integers), sacrificing a bit to use as a mask will significantly reduce the range of values it can represent.

NumPy does have support for masked arrays—that is, arrays that have a separate Boolean mask array attached for marking data as "good" or "bad." Pandas could have derived from this, but the overhead in both storage, computation, and code maintenance makes that an unattractive choice.

With these constraints in mind, Pandas chose to use sentinels for missing data, and further chose to use two already-existing Python null values: the special floating-point `NaN` value, and the Python `None` object. This choice has some side effects, as we will see, but in practice ends up being a good compromise in most cases of interest.

None: Pythonic missing data

The first sentinel value used by Pandas is `None`, a Python singleton object that is often used for missing data in Python code. Because `None` is a Python object, it cannot be used in any arbitrary NumPy/Pandas array, but only in arrays with data type `'object'` (i.e., arrays of Python objects):

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

In[2]: vals1 = np.array([1, None, 3, 4])
       vals1

Out[2]: array([1, None, 3, 4], dtype=object)
```

This `dtype=object` means that the best common type representation NumPy could infer for the contents of the array is that they are Python objects. While this kind of object array is useful for some purposes, any operations on the data will be done at the Python level, with much more overhead than the typically fast operations seen for arrays with native types:

```
In[3]: for dtype in ['object', 'int']:
           print("dtype =", dtype)
           %timeit np.arange(1E6, dtype=dtype).sum()
           print()

dtype = object
10 loops, best of 3: 78.2 ms per loop

dtype = int
100 loops, best of 3: 3.06 ms per loop
```

The use of Python objects in an array also means that if you perform aggregations like `sum()` or `min()` across an array with a `None` value, you will generally get an error:

```
In[4]: vals1.sum()

TypeError                                 Traceback (most recent call last)

<ipython-input-4-749fd8ae6030> in <module>()
----> 1 vals1.sum()


/Users/jakevdp/anaconda/lib/python3.5/site-packages/numpy/core/_methods.py ...
     30
     31 def _sum(a, axis=None, dtype=None, out=None, keepdims=False):
---> 32     return umr_sum(a, axis, dtype, out, keepdims)
     33
     34 def _prod(a, axis=None, dtype=None, out=None, keepdims=False):


TypeError: unsupported operand type(s) for +: 'int' and 'NoneType'
```

This reflects the fact that addition between an integer and `None` is undefined.

NaN: Missing numerical data

The other missing data representation, `NaN` (acronym for *Not a Number*), is different; it is a special floating-point value recognized by all systems that use the standard IEEE floating-point representation:

```
In[5]: vals2 = np.array([1, np.nan, 3, 4])
       vals2.dtype

Out[5]: dtype('float64')
```

Notice that NumPy chose a native floating-point type for this array: this means that unlike the object array from before, this array supports fast operations pushed into compiled code. You should be aware that `NaN` is a bit like a data virus—it infects any other object it touches. Regardless of the operation, the result of arithmetic with `NaN` will be another `NaN`:

```
In[6]: 1 + np.nan

Out[6]: nan

In[7]: 0 *  np.nan

Out[7]: nan
```

Note that this means that aggregates over the values are well defined (i.e., they don't result in an error) but not always useful:

```
In[8]: vals2.sum(), vals2.min(), vals2.max()

Out[8]: (nan, nan, nan)
```

NumPy does provide some special aggregations that will ignore these missing values:

```
In[9]: np.nansum(vals2), np.nanmin(vals2), np.nanmax(vals2)
```

```
Out[9]: (8.0, 1.0, 4.0)
```

Keep in mind that `NaN` is specifically a floating-point value; there is no equivalent NaN value for integers, strings, or other types.

NaN and None in Pandas

`NaN` and `None` both have their place, and Pandas is built to handle the two of them nearly interchangeably, converting between them where appropriate:

```
In[10]: pd.Series([1, np.nan, 2, None])
```

```
Out[10]: 0    1.0
         1    NaN
         2    2.0
         3    NaN
         dtype: float64
```

For types that don't have an available sentinel value, Pandas automatically type-casts when NA values are present. For example, if we set a value in an integer array to `np.nan`, it will automatically be upcast to a floating-point type to accommodate the NA:

```
In[11]: x = pd.Series(range(2), dtype=int)
        x
```

```
Out[11]: 0    0
         1    1
         dtype: int64
```

```
In[12]: x[0] = None
        x
```

```
Out[12]: 0    NaN
         1    1.0
         dtype: float64
```

Notice that in addition to casting the integer array to floating point, Pandas automatically converts the `None` to a `NaN` value. (Be aware that there is a proposal to add a native integer NA to Pandas in the future; as of this writing, it has not been included.)

While this type of magic may feel a bit hackish compared to the more unified approach to NA values in domain-specific languages like R, the Pandas sentinel/casting approach works quite well in practice and in my experience only rarely causes issues.

Table 3-2 lists the upcasting conventions in Pandas when NA values are introduced.

Table 3-2. Pandas handling of NAs by type

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`
`boolean`	Cast to `object`	`None` or `np.nan`

Keep in mind that in Pandas, string data is always stored with an `object` dtype.

Operating on Null Values

As we have seen, Pandas treats `None` and `NaN` as essentially interchangeable for indicating missing or null values. To facilitate this convention, there are several useful methods for detecting, removing, and replacing null values in Pandas data structures. They are:

`isnull()`
: Generate a Boolean mask indicating missing values

`notnull()`
: Opposite of `isnull()`

`dropna()`
: Return a filtered version of the data

`fillna()`
: Return a copy of the data with missing values filled or imputed

We will conclude this section with a brief exploration and demonstration of these routines.

Detecting null values

Pandas data structures have two useful methods for detecting null data: `isnull()` and `notnull()`. Either one will return a Boolean mask over the data. For example:

```
In[13]: data = pd.Series([1, np.nan, 'hello', None])
```

```
In[14]: data.isnull()
```

```
Out[14]: 0    False
         1     True
         2    False
         3     True
         dtype: bool
```

As mentioned in "Data Indexing and Selection" on page 107, Boolean masks can be used directly as a `Series` or `DataFrame` index:

```
In[15]: data[data.notnull()]
```

```
Out[15]: 0        1
         2    hello
         dtype: object
```

The `isnull()` and `notnull()` methods produce similar Boolean results for `DataFrame`s.

Dropping null values

In addition to the masking used before, there are the convenience methods, `dropna()` (which removes NA values) and `fillna()` (which fills in NA values). For a `Series`, the result is straightforward:

```
In[16]: data.dropna()
```

```
Out[16]: 0        1
         2    hello
         dtype: object
```

For a `DataFrame`, there are more options. Consider the following `DataFrame`:

```
In[17]: df = pd.DataFrame([[1,      np.nan, 2],
                           [2,      3,      5],
                           [np.nan, 4,      6]])
        df
```

```
Out[17]:      0    1  2
         0  1.0  NaN  2
         1  2.0  3.0  5
         2  NaN  4.0  6
```

We cannot drop single values from a `DataFrame`; we can only drop full rows or full columns. Depending on the application, you might want one or the other, so `dropna()` gives a number of options for a `DataFrame`.

By default, `dropna()` will drop all rows in which *any* null value is present:

```
In[18]: df.dropna()
```

```
Out[18]:      0    1  2
         1  2.0  3.0  5
```

Alternatively, you can drop NA values along a different axis; `axis=1` drops all columns containing a null value:

```
In[19]: df.dropna(axis='columns')
```

```
Out[19]:    2
         0  2
         1  5
         2  6
```

But this drops some good data as well; you might rather be interested in dropping rows or columns with *all* NA values, or a majority of NA values. This can be specified through the `how` or `thresh` parameters, which allow fine control of the number of nulls to allow through.

The default is `how='any'`, such that any row or column (depending on the `axis` keyword) containing a null value will be dropped. You can also specify `how='all'`, which will only drop rows/columns that are *all* null values:

```
In[20]: df[3] = np.nan
        df

Out[20]:      0    1  2   3
         0  1.0  NaN  2 NaN
         1  2.0  3.0  5 NaN
         2  NaN  4.0  6 NaN

In[21]: df.dropna(axis='columns', how='all')

Out[21]:      0    1  2
         0  1.0  NaN  2
         1  2.0  3.0  5
         2  NaN  4.0  6
```

For finer-grained control, the `thresh` parameter lets you specify a minimum number of non-null values for the row/column to be kept:

```
In[22]: df.dropna(axis='rows', thresh=3)

Out[22]:      0    1  2   3
         1  2.0  3.0  5 NaN
```

Here the first and last row have been dropped, because they contain only two non-null values.

Filling null values

Sometimes rather than dropping NA values, you'd rather replace them with a valid value. This value might be a single number like zero, or it might be some sort of imputation or interpolation from the good values. You could do this in-place using the `isnull()` method as a mask, but because it is such a common operation Pandas provides the `fillna()` method, which returns a copy of the array with the null values replaced.

Consider the following `Series`:

```
In[23]: data = pd.Series([1, np.nan, 2, None, 3], index=list('abcde'))
        data

Out[23]: a    1.0
         b    NaN
         c    2.0
         d    NaN
```

```
e    3.0
dtype: float64
```

We can fill NA entries with a single value, such as zero:

```
In[24]: data.fillna(0)

Out[24]: a    1.0
         b    0.0
         c    2.0
         d    0.0
         e    3.0
         dtype: float64
```

We can specify a forward-fill to propagate the previous value forward:

```
In[25]: # forward-fill
        data.fillna(method='ffill')

Out[25]: a    1.0
         b    1.0
         c    2.0
         d    2.0
         e    3.0
         dtype: float64
```

Or we can specify a back-fill to propagate the next values backward:

```
In[26]: # back-fill
        data.fillna(method='bfill')

Out[26]: a    1.0
         b    2.0
         c    2.0
         d    3.0
         e    3.0
         dtype: float64
```

For `DataFrame`s, the options are similar, but we can also specify an `axis` along which the fills take place:

```
In[27]: df

Out[27]:      0    1  2   3
         0  1.0  NaN  2 NaN
         1  2.0  3.0  5 NaN
         2  NaN  4.0  6 NaN

In[28]: df.fillna(method='ffill', axis=1)

Out[28]:      0    1    2    3
         0  1.0  1.0  2.0  2.0
         1  2.0  3.0  5.0  5.0
         2  NaN  4.0  6.0  6.0
```

Notice that if a previous value is not available during a forward fill, the NA value remains.

Hierarchical Indexing

Up to this point we've been focused primarily on one-dimensional and two-dimensional data, stored in Pandas `Series` and `DataFrame` objects, respectively. Often it is useful to go beyond this and store higher-dimensional data—that is, data indexed by more than one or two keys. While Pandas does provide `Panel` and `Panel4D` objects that natively handle three-dimensional and four-dimensional data (see "Panel Data" on page 141), a far more common pattern in practice is to make use of *hierarchical indexing* (also known as *multi-indexing*) to incorporate multiple index *levels* within a single index. In this way, higher-dimensional data can be compactly represented within the familiar one-dimensional `Series` and two-dimensional `DataFrame` objects.

In this section, we'll explore the direct creation of `MultiIndex` objects; considerations around indexing, slicing, and computing statistics across multiply indexed data; and useful routines for converting between simple and hierarchically indexed representations of your data.

We begin with the standard imports:

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

A Multiply Indexed Series

Let's start by considering how we might represent two-dimensional data within a one-dimensional `Series`. For concreteness, we will consider a series of data where each point has a character and numerical key.

The bad way

Suppose you would like to track data about states from two different years. Using the Pandas tools we've already covered, you might be tempted to simply use Python tuples as keys:

```
In[2]: index = [('California', 2000), ('California', 2010),
                ('New York', 2000), ('New York', 2010),
                ('Texas', 2000), ('Texas', 2010)]
       populations = [33871648, 37253956,
                      18976457, 19378102,
                      20851820, 25145561]
       pop = pd.Series(populations, index=index)
       pop

Out[2]: (California, 2000)    33871648
        (California, 2010)    37253956
        (New York, 2000)      18976457
        (New York, 2010)      19378102
        (Texas, 2000)         20851820
```

```
        (Texas, 2010)        25145561
        dtype: int64
```

With this indexing scheme, you can straightforwardly index or slice the series based on this multiple index:

```
In[3]: pop[('California', 2010):('Texas', 2000)]

Out[3]: (California, 2010)    37253956
        (New York, 2000)      18976457
        (New York, 2010)      19378102
        (Texas, 2000)         20851820
        dtype: int64
```

But the convenience ends there. For example, if you need to select all values from 2010, you'll need to do some messy (and potentially slow) munging to make it happen:

```
In[4]: pop[[i for i in pop.index if i[1] == 2010]]

Out[4]: (California, 2010)    37253956
        (New York, 2010)      19378102
        (Texas, 2010)         25145561
        dtype: int64
```

This produces the desired result, but is not as clean (or as efficient for large datasets) as the slicing syntax we've grown to love in Pandas.

The better way: Pandas MultiIndex

Fortunately, Pandas provides a better way. Our tuple-based indexing is essentially a rudimentary multi-index, and the Pandas `MultiIndex` type gives us the type of operations we wish to have. We can create a multi-index from the tuples as follows:

```
In[5]: index = pd.MultiIndex.from_tuples(index)
       index

Out[5]: MultiIndex(levels=[['California', 'New York', 'Texas'], [2000, 2010]],
                   labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])
```

Notice that the `MultiIndex` contains multiple *levels* of indexing—in this case, the state names and the years, as well as multiple *labels* for each data point which encode these levels.

If we reindex our series with this `MultiIndex`, we see the hierarchical representation of the data:

```
In[6]: pop = pop.reindex(index)
       pop

Out[6]: California  2000    33871648
                    2010    37253956
        New York    2000    18976457
                    2010    19378102
```

```
Texas       2000    20851820
            2010    25145561
dtype: int64
```

Here the first two columns of the Series representation show the multiple index values, while the third column shows the data. Notice that some entries are missing in the first column: in this multi-index representation, any blank entry indicates the same value as the line above it.

Now to access all data for which the second index is 2010, we can simply use the Pandas slicing notation:

```
In[7]: pop[:, 2010]
```

```
Out[7]: California    37253956
        New York      19378102
        Texas         25145561
        dtype: int64
```

The result is a singly indexed array with just the keys we're interested in. This syntax is much more convenient (and the operation is much more efficient!) than the homespun tuple-based multi-indexing solution that we started with. We'll now further discuss this sort of indexing operation on hierarchically indexed data.

MultiIndex as extra dimension

You might notice something else here: we could easily have stored the same data using a simple DataFrame with index and column labels. In fact, Pandas is built with this equivalence in mind. The unstack() method will quickly convert a multiply-indexed Series into a conventionally indexed DataFrame:

```
In[8]: pop_df = pop.unstack()
       pop_df
```

```
Out[8]:                 2000      2010
        California  33871648  37253956
        New York    18976457  19378102
        Texas       20851820  25145561
```

Naturally, the stack() method provides the opposite operation:

```
In[9]: pop_df.stack()
```

```
Out[9]:  California  2000    33871648
                     2010    37253956
         New York    2000    18976457
                     2010    19378102
         Texas       2000    20851820
                     2010    25145561
         dtype: int64
```

Seeing this, you might wonder why would we would bother with hierarchical indexing at all. The reason is simple: just as we were able to use multi-indexing to represent two-dimensional data within a one-dimensional Series, we can also use it to represent data of three or more dimensions in a Series or DataFrame. Each extra level in a multi-index represents an extra dimension of data; taking advantage of this property gives us much more flexibility in the types of data we can represent. Concretely, we might want to add another column of demographic data for each state at each year (say, population under 18); with a MultiIndex this is as easy as adding another column to the DataFrame:

```
In[10]: pop_df = pd.DataFrame({'total': pop,
                               'under18': [9267089, 9284094,
                                           4687374, 4318033,
                                           5906301, 6879014]})
        pop_df

Out[10]:                    total  under18
         California 2000  33871648  9267089
                    2010  37253956  9284094
         New York   2000  18976457  4687374
                    2010  19378102  4318033
         Texas      2000  20851820  5906301
                    2010  25145561  6879014
```

In addition, all the ufuncs and other functionality discussed in "Operating on Data in Pandas" on page 115 work with hierarchical indices as well. Here we compute the fraction of people under 18 by year, given the above data:

```
In[11]: f_u18 = pop_df['under18'] / pop_df['total']
        f_u18.unstack()

Out[11]:                2000      2010
         California  0.273594  0.249211
         New York    0.247010  0.222831
         Texas       0.283251  0.273568
```

This allows us to easily and quickly manipulate and explore even high-dimensional data.

Methods of MultiIndex Creation

The most straightforward way to construct a multiply indexed Series or DataFrame is to simply pass a list of two or more index arrays to the constructor. For example:

```
In[12]: df = pd.DataFrame(np.random.rand(4, 2),
                          index=[['a', 'a', 'b', 'b'], [1, 2, 1, 2]],
                          columns=['data1', 'data2'])
        df

Out[12]:        data1     data2
         a 1  0.554233  0.356072
           2  0.925244  0.219474
         b 1  0.441759  0.610054
           2  0.171495  0.886688
```

The work of creating the `MultiIndex` is done in the background.

Similarly, if you pass a dictionary with appropriate tuples as keys, Pandas will automatically recognize this and use a `MultiIndex` by default:

```
In[13]: data = {('California', 2000): 33871648,
                ('California', 2010): 37253956,
                ('Texas', 2000): 20851820,
                ('Texas', 2010): 25145561,
                ('New York', 2000): 18976457,
                ('New York', 2010): 19378102}
        pd.Series(data)
```

```
Out[13]: California  2000    33871648
                     2010    37253956
         New York    2000    18976457
                     2010    19378102
         Texas       2000    20851820
                     2010    25145561
         dtype: int64
```

Nevertheless, it is sometimes useful to explicitly create a `MultiIndex`; we'll see a couple of these methods here.

Explicit MultiIndex constructors

For more flexibility in how the index is constructed, you can instead use the class method constructors available in the `pd.MultiIndex`. For example, as we did before, you can construct the `MultiIndex` from a simple list of arrays, giving the index values within each level:

```
In[14]: pd.MultiIndex.from_arrays([['a', 'a', 'b', 'b'], [1, 2, 1, 2]])
```

```
Out[14]: MultiIndex(levels=[['a', 'b'], [1, 2]],
                    labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

You can construct it from a list of tuples, giving the multiple index values of each point:

```
In[15]: pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('b', 1), ('b', 2)])
```

```
Out[15]: MultiIndex(levels=[['a', 'b'], [1, 2]],
                    labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

You can even construct it from a Cartesian product of single indices:

```
In[16]: pd.MultiIndex.from_product([['a', 'b'], [1, 2]])
```

```
Out[16]: MultiIndex(levels=[['a', 'b'], [1, 2]],
                    labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

Similarly, you can construct the `MultiIndex` directly using its internal encoding by passing `levels` (a list of lists containing available index values for each level) and `labels` (a list of lists that reference these labels):

```
In[17]: pd.MultiIndex(levels=[['a', 'b'], [1, 2]],
                      labels=[[0, 0, 1, 1], [0, 1, 0, 1]])

Out[17]: MultiIndex(levels=[['a', 'b'], [1, 2]],
                    labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

You can pass any of these objects as the `index` argument when creating a `Series` or `DataFrame`, or to the `reindex` method of an existing `Series` or `DataFrame`.

MultiIndex level names

Sometimes it is convenient to name the levels of the `MultiIndex`. You can accomplish this by passing the `names` argument to any of the above `MultiIndex` constructors, or by setting the `names` attribute of the index after the fact:

```
In[18]: pop.index.names = ['state', 'year']
        pop

Out[18]: state       year
         California  2000    33871648
                     2010    37253956
         New York    2000    18976457
                     2010    19378102
         Texas       2000    20851820
                     2010    25145561
         dtype: int64
```

With more involved datasets, this can be a useful way to keep track of the meaning of various index values.

MultiIndex for columns

In a `DataFrame`, the rows and columns are completely symmetric, and just as the rows can have multiple levels of indices, the columns can have multiple levels as well. Consider the following, which is a mock-up of some (somewhat realistic) medical data:

```
In[19]:
# hierarchical indices and columns
index = pd.MultiIndex.from_product([[2013, 2014], [1, 2]],
                                   names=['year', 'visit'])
columns = pd.MultiIndex.from_product([['Bob', 'Guido', 'Sue'], ['HR', 'Temp']],
                                     names=['subject', 'type'])

# mock some data
data = np.round(np.random.randn(4, 6), 1)
data[:, ::2] *= 10
data += 37

# create the DataFrame
health_data = pd.DataFrame(data, index=index, columns=columns)
health_data
```

```
Out[19]: subject      Bob       Guido         Sue
         type          HR  Temp    HR  Temp    HR  Temp
         year visit
         2013 1      31.0  38.7  32.0  36.7  35.0  37.2
              2      44.0  37.7  50.0  35.0  29.0  36.7
         2014 1      30.0  37.4  39.0  37.8  61.0  36.9
              2      47.0  37.8  48.0  37.3  51.0  36.5
```

Here we see where the multi-indexing for both rows and columns can come in *very* handy. This is fundamentally four-dimensional data, where the dimensions are the subject, the measurement type, the year, and the visit number. With this in place we can, for example, index the top-level column by the person's name and get a full `DataFrame` containing just that person's information:

```
In[20]: health_data['Guido']
```

```
Out[20]: type          HR  Temp
         year visit
         2013 1      32.0  36.7
              2      50.0  35.0
         2014 1      39.0  37.8
              2      48.0  37.3
```

For complicated records containing multiple labeled measurements across multiple times for many subjects (people, countries, cities, etc.), use of hierarchical rows and columns can be extremely convenient!

Indexing and Slicing a MultiIndex

Indexing and slicing on a `MultiIndex` is designed to be intuitive, and it helps if you think about the indices as added dimensions. We'll first look at indexing multiply indexed `Series`, and then multiply indexed `DataFrames`.

Multiply indexed Series

Consider the multiply indexed `Series` of state populations we saw earlier:

```
In[21]: pop
```

```
Out[21]: state       year
         California  2000    33871648
                     2010    37253956
         New York    2000    18976457
                     2010    19378102
         Texas       2000    20851820
                     2010    25145561
         dtype: int64
```

We can access single elements by indexing with multiple terms:

```
In[22]: pop['California', 2000]
```

```
Out[22]: 33871648
```

The `MultiIndex` also supports *partial indexing*, or indexing just one of the levels in the index. The result is another `Series`, with the lower-level indices maintained:

```
In[23]: pop['California']
```

```
Out[23]: year
         2000    33871648
         2010    37253956
         dtype: int64
```

Partial slicing is available as well, as long as the `MultiIndex` is sorted (see discussion in "Sorted and unsorted indices" on page 137):

```
In[24]: pop.loc['California':'New York']
```

```
Out[24]: state       year
         California  2000    33871648
                     2010    37253956
         New York    2000    18976457
                     2010    19378102
         dtype: int64
```

With sorted indices, we can perform partial indexing on lower levels by passing an empty slice in the first index:

```
In[25]: pop[:, 2000]
```

```
Out[25]: state
         California    33871648
         New York      18976457
         Texas         20851820
         dtype: int64
```

Other types of indexing and selection (discussed in "Data Indexing and Selection" on page 107) work as well; for example, selection based on Boolean masks:

```
In[26]: pop[pop > 22000000]
```

```
Out[26]: state       year
         California  2000    33871648
                     2010    37253956
         Texas       2010    25145561
         dtype: int64
```

Selection based on fancy indexing also works:

```
In[27]: pop[['California', 'Texas']]
```

```
Out[27]: state       year
         California  2000    33871648
                     2010    37253956
         Texas       2000    20851820
                     2010    25145561
         dtype: int64
```

Multiply indexed DataFrames

A multiply indexed `DataFrame` behaves in a similar manner. Consider our toy medical `DataFrame` from before:

```
In[28]: health_data

Out[28]: subject      Bob       Guido         Sue
         type          HR  Temp    HR  Temp    HR  Temp
         year visit
         2013 1      31.0  38.7  32.0  36.7  35.0  37.2
              2      44.0  37.7  50.0  35.0  29.0  36.7
         2014 1      30.0  37.4  39.0  37.8  61.0  36.9
              2      47.0  37.8  48.0  37.3  51.0  36.5
```

Remember that columns are primary in a `DataFrame`, and the syntax used for multiply indexed `Series` applies to the columns. For example, we can recover Guido's heart rate data with a simple operation:

```
In[29]: health_data['Guido', 'HR']

Out[29]: year  visit
         2013  1        32.0
               2        50.0
         2014  1        39.0
               2        48.0
         Name: (Guido, HR), dtype: float64
```

Also, as with the single-index case, we can use the `loc`, `iloc`, and `ix` indexers introduced in "Data Indexing and Selection" on page 107. For example:

```
In[30]: health_data.iloc[:2, :2]

Out[30]: subject      Bob
         type          HR  Temp
         year visit
         2013 1      31.0  38.7
              2      44.0  37.7
```

These indexers provide an array-like view of the underlying two-dimensional data, but each individual index in `loc` or `iloc` can be passed a tuple of multiple indices. For example:

```
In[31]: health_data.loc[:, ('Bob', 'HR')]

Out[31]: year  visit
         2013  1        31.0
               2        44.0
         2014  1        30.0
               2        47.0
         Name: (Bob, HR), dtype: float64
```

Working with slices within these index tuples is not especially convenient; trying to create a slice within a tuple will lead to a syntax error:

```
In[32]: health_data.loc[(:, 1), (:, 'HR')]

  File "<ipython-input-32-8e3cc151e316>", line 1
    health_data.loc[(:, 1), (:, 'HR')]
                     ^
SyntaxError: invalid syntax
```

You could get around this by building the desired slice explicitly using Python's built-in `slice()` function, but a better way in this context is to use an `IndexSlice` object, which Pandas provides for precisely this situation. For example:

```
In[33]: idx = pd.IndexSlice
        health_data.loc[idx[:, 1], idx[:, 'HR']]

Out[33]: subject      Bob Guido   Sue
         type          HR    HR    HR
         year visit
         2013 1      31.0  32.0  35.0
         2014 1      30.0  39.0  61.0
```

There are so many ways to interact with data in multiply indexed `Series` and `DataFrame`s, and as with many tools in this book the best way to become familiar with them is to try them out!

Rearranging Multi-Indices

One of the keys to working with multiply indexed data is knowing how to effectively transform the data. There are a number of operations that will preserve all the information in the dataset, but rearrange it for the purposes of various computations. We saw a brief example of this in the `stack()` and `unstack()` methods, but there are many more ways to finely control the rearrangement of data between hierarchical indices and columns, and we'll explore them here.

Sorted and unsorted indices

Earlier, we briefly mentioned a caveat, but we should emphasize it more here. *Many of the* `MultiIndex` *slicing operations will fail if the index is not sorted.* Let's take a look at this here.

We'll start by creating some simple multiply indexed data where the indices are *not lexographically sorted*:

```
In[34]: index = pd.MultiIndex.from_product([['a', 'c', 'b'], [1, 2]])
        data = pd.Series(np.random.rand(6), index=index)
        data.index.names = ['char', 'int']
        data

Out[34]: char  int
         a     1      0.003001
               2      0.164974
         c     1      0.741650
```

```
        2      0.569264
b       1      0.001693
        2      0.526226
dtype: float64
```

If we try to take a partial slice of this index, it will result in an error:

```
In[35]: try:
            data['a':'b']
        except KeyError as e:
            print(type(e))
            print(e)

<class 'KeyError'>
'Key length (1) was greater than MultiIndex lexsort depth (0)'
```

Although it is not entirely clear from the error message, this is the result of the `MultiIndex` not being sorted. For various reasons, partial slices and other similar operations require the levels in the `MultiIndex` to be in sorted (i.e., lexographical) order. Pandas provides a number of convenience routines to perform this type of sorting; examples are the `sort_index()` and `sortlevel()` methods of the `DataFrame`. We'll use the simplest, `sort_index()`, here:

```
In[36]: data = data.sort_index()
        data

Out[36]: char  int
         a     1      0.003001
               2      0.164974
         b     1      0.001693
               2      0.526226
         c     1      0.741650
               2      0.569264
         dtype: float64
```

With the index sorted in this way, partial slicing will work as expected:

```
In[37]: data['a':'b']

Out[37]: char  int
         a     1      0.003001
               2      0.164974
         b     1      0.001693
               2      0.526226
         dtype: float64
```

Stacking and unstacking indices

As we saw briefly before, it is possible to convert a dataset from a stacked multi-index to a simple two-dimensional representation, optionally specifying the level to use:

```
In[38]: pop.unstack(level=0)
```

```
Out[38]:  state  California   New York     Texas
          year
          2000     33871648   18976457  20851820
          2010     37253956   19378102  25145561
```

```
In[39]: pop.unstack(level=1)
```

```
Out[39]: year            2000      2010
         state
         California  33871648  37253956
         New York    18976457  19378102
         Texas       20851820  25145561
```

The opposite of `unstack()` is `stack()`, which here can be used to recover the original series:

```
In[40]: pop.unstack().stack()
```

```
Out[40]: state       year
         California  2000    33871648
                     2010    37253956
         New York    2000    18976457
                     2010    19378102
         Texas       2000    20851820
                     2010    25145561
         dtype: int64
```

Index setting and resetting

Another way to rearrange hierarchical data is to turn the index labels into columns; this can be accomplished with the `reset_index` method. Calling this on the population dictionary will result in a `DataFrame` with a *state* and *year* column holding the information that was formerly in the index. For clarity, we can optionally specify the name of the data for the column representation:

```
In[41]: pop_flat = pop.reset_index(name='population')
        pop_flat
```

```
Out[41]:         state  year  population
         0  California  2000    33871648
         1  California  2010    37253956
         2    New York  2000    18976457
         3    New York  2010    19378102
         4       Texas  2000    20851820
         5       Texas  2010    25145561
```

Often when you are working with data in the real world, the raw input data looks like this and it's useful to build a `MultiIndex` from the column values. This can be done with the `set_index` method of the `DataFrame`, which returns a multiply indexed `DataFrame`:

```
In[42]: pop_flat.set_index(['state', 'year'])
```

```
Out[42]:                  population
        state      year
        California 2000    33871648
                   2010    37253956
        New York   2000    18976457
                   2010    19378102
        Texas      2000    20851820
                   2010    25145561
```

In practice, I find this type of reindexing to be one of the more useful patterns when I encounter real-world datasets.

Data Aggregations on Multi-Indices

We've previously seen that Pandas has built-in data aggregation methods, such as `mean()`, `sum()`, and `max()`. For hierarchically indexed data, these can be passed a `level` parameter that controls which subset of the data the aggregate is computed on.

For example, let's return to our health data:

```
In[43]: health_data
```

```
Out[43]:  subject      Bob       Guido         Sue
          type          HR  Temp    HR  Temp    HR  Temp
          year visit
          2013 1      31.0  38.7  32.0  36.7  35.0  37.2
               2      44.0  37.7  50.0  35.0  29.0  36.7
          2014 1      30.0  37.4  39.0  37.8  61.0  36.9
               2      47.0  37.8  48.0  37.3  51.0  36.5
```

Perhaps we'd like to average out the measurements in the two visits each year. We can do this by naming the index level we'd like to explore, in this case the year:

```
In[44]: data_mean = health_data.mean(level='year')
        data_mean
```

```
Out[44]: subject   Bob       Guido          Sue
         type       HR  Temp    HR   Temp    HR   Temp
         year
         2013     37.5  38.2  41.0  35.85  32.0  36.95
         2014     38.5  37.6  43.5  37.55  56.0  36.70
```

By further making use of the `axis` keyword, we can take the mean among levels on the columns as well:

```
In[45]: data_mean.mean(axis=1, level='type')
```

```
Out[45]: type         HR       Temp
         year
         2013  36.833333  37.000000
         2014  46.000000  37.283333
```

Thus in two lines, we've been able to find the average heart rate and temperature measured among all subjects in all visits each year. This syntax is actually a shortcut to the GroupBy functionality, which we will discuss in "Aggregation and Grouping" on page 158. While this is a toy example, many real-world datasets have similar hierarchical structure.

Panel Data

Pandas has a few other fundamental data structures that we have not yet discussed, namely the `pd.Panel` and `pd.Panel4D` objects. These can be thought of, respectively, as three-dimensional and four-dimensional generalizations of the (one-dimensional) `Series` and (two-dimensional) `DataFrame` structures. Once you are familiar with indexing and manipulation of data in a `Series` and `DataFrame`, `Panel` and `Panel4D` are relatively straightforward to use. In particular, the `ix`, `loc`, and `iloc` indexers discussed in "Data Indexing and Selection" on page 107 extend readily to these higher-dimensional structures.

We won't cover these panel structures further in this text, as I've found in the majority of cases that multi-indexing is a more useful and conceptually simpler representation for higher-dimensional data. Additionally, panel data is fundamentally a dense data representation, while multi-indexing is fundamentally a sparse data representation. As the number of dimensions increases, the dense representation can become very inefficient for the majority of real-world datasets. For the occasional specialized application, however, these structures can be useful. If you'd like to read more about the `Panel` and `Panel4D` structures, see the references listed in "Further Resources" on page 215.

Combining Datasets: Concat and Append

Some of the most interesting studies of data come from combining different data sources. These operations can involve anything from very straightforward concatenation of two different datasets, to more complicated database-style joins and merges that correctly handle any overlaps between the datasets. `Series` and `DataFrame`s are built with this type of operation in mind, and Pandas includes functions and methods that make this sort of data wrangling fast and straightforward.

Here we'll take a look at simple concatenation of `Series` and `DataFrame`s with the `pd.concat` function; later we'll dive into more sophisticated in-memory merges and joins implemented in Pandas.

We begin with the standard imports:

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

For convenience, we'll define this function, which creates a DataFrame of a particular form that will be useful below:

```
In[2]: def make_df(cols, ind):
           """Quickly make a DataFrame"""
           data = {c: [str(c) + str(i) for i in ind]
                   for c in cols}
           return pd.DataFrame(data, ind)

       # example DataFrame
       make_df('ABC', range(3))
```

```
Out[2]:     A   B   C
        0  A0  B0  C0
        1  A1  B1  C1
        2  A2  B2  C2
```

Recall: Concatenation of NumPy Arrays

Concatenation of Series and DataFrame objects is very similar to concatenation of NumPy arrays, which can be done via the np.concatenate function as discussed in "The Basics of NumPy Arrays" on page 42. Recall that with it, you can combine the contents of two or more arrays into a single array:

```
In[4]: x = [1, 2, 3]
       y = [4, 5, 6]
       z = [7, 8, 9]
       np.concatenate([x, y, z])
```

```
Out[4]: array([1, 2, 3, 4, 5, 6, 7, 8, 9])
```

The first argument is a list or tuple of arrays to concatenate. Additionally, it takes an axis keyword that allows you to specify the axis along which the result will be concatenated:

```
In[5]: x = [[1, 2],
            [3, 4]]
       np.concatenate([x, x], axis=1)
```

```
Out[5]: array([[1, 2, 1, 2],
               [3, 4, 3, 4]])
```

Simple Concatenation with pd.concat

Pandas has a function, pd.concat(), which has a similar syntax to np.concatenate but contains a number of options that we'll discuss momentarily:

```
# Signature in Pandas v0.18
pd.concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False,
          keys=None, levels=None, names=None, verify_integrity=False,
          copy=True)
```

`pd.concat()` can be used for a simple concatenation of `Series` or `DataFrame` objects, just as `np.concatenate()` can be used for simple concatenations of arrays:

```
In[6]: ser1 = pd.Series(['A', 'B', 'C'], index=[1, 2, 3])
       ser2 = pd.Series(['D', 'E', 'F'], index=[4, 5, 6])
       pd.concat([ser1, ser2])

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

It also works to concatenate higher-dimensional objects, such as `DataFrame`s:

```
In[7]: df1 = make_df('AB', [1, 2])
       df2 = make_df('AB', [3, 4])
       print(df1); print(df2); print(pd.concat([df1, df2]))

df1             df2            pd.concat([df1, df2])
     A   B           A   B          A   B
 1  A1  B1       3  A3  B3       1  A1  B1
 2  A2  B2       4  A4  B4       2  A2  B2
                                 3  A3  B3
                                 4  A4  B4
```

By default, the concatenation takes place row-wise within the `DataFrame` (i.e., `axis=0`). Like `np.concatenate`, `pd.concat` allows specification of an axis along which concatenation will take place. Consider the following example:

```
In[8]: df3 = make_df('AB', [0, 1])
       df4 = make_df('CD', [0, 1])
       print(df3); print(df4); print(pd.concat([df3, df4], axis='col'))

df3             df4            pd.concat([df3, df4], axis='col')
     A   B           C   D          A   B   C   D
 0  A0  B0       0  C0  D0      0  A0  B0  C0  D0
 1  A1  B1       1  C1  D1      1  A1  B1  C1  D1
```

We could have equivalently specified `axis=1`; here we've used the more intuitive `axis='col'`.

Duplicate indices

One important difference between `np.concatenate` and `pd.concat` is that Pandas concatenation *preserves indices*, even if the result will have duplicate indices! Consider this simple example:

```
In[9]: x = make_df('AB', [0, 1])
       y = make_df('AB', [2, 3])
```

```
y.index = x.index  # make duplicate indices!
print(x); print(y); print(pd.concat([x, y]))
```

```
x             y             pd.concat([x, y])
    A   B         A   B          A   B
 0  A0  B0     0  A2  B2     0  A0  B0
 1  A1  B1     1  A3  B3     1  A1  B1
                             0  A2  B2
                             1  A3  B3
```

Notice the repeated indices in the result. While this is valid within `DataFrames`, the outcome is often undesirable. `pd.concat()` gives us a few ways to handle it.

Catching the repeats as an error. If you'd like to simply verify that the indices in the result of `pd.concat()` do not overlap, you can specify the `verify_integrity` flag. With this set to `True`, the concatenation will raise an exception if there are duplicate indices. Here is an example, where for clarity we'll catch and print the error message:

```
In[10]: try:
            pd.concat([x, y], verify_integrity=True)
        except ValueError as e:
            print("ValueError:", e)

ValueError: Indexes have overlapping values: [0, 1]
```

Ignoring the index. Sometimes the index itself does not matter, and you would prefer it to simply be ignored. You can specify this option using the `ignore_index` flag. With this set to `True`, the concatenation will create a new integer index for the resulting `Series`:

```
In[11]: print(x); print(y); print(pd.concat([x, y], ignore_index=True))
```

```
x             y             pd.concat([x, y], ignore_index=True)
    A   B         A   B          A   B
 0  A0  B0     0  A2  B2     0  A0  B0
 1  A1  B1     1  A3  B3     1  A1  B1
                             2  A2  B2
                             3  A3  B3
```

Adding MultiIndex keys. Another alternative is to use the `keys` option to specify a label for the data sources; the result will be a hierarchically indexed series containing the data:

```
In[12]: print(x); print(y); print(pd.concat([x, y], keys=['x', 'y']))
```

```
x               y               pd.concat([x, y], keys=['x', 'y'])
    A   B           A   B               A   B
 0  A0  B0       0  A2  B2       x  0  A0  B0
 1  A1  B1       1  A3  B3          1  A1  B1
                                 y  0  A2  B2
                                    1  A3  B3
```

The result is a multiply indexed DataFrame, and we can use the tools discussed in "Hierarchical Indexing" on page 128 to transform this data into the representation we're interested in.

Concatenation with joins

In the simple examples we just looked at, we were mainly concatenating DataFrames with shared column names. In practice, data from different sources might have different sets of column names, and pd.concat offers several options in this case. Consider the concatenation of the following two DataFrames, which have some (but not all!) columns in common:

```
In[13]: df5 = make_df('ABC', [1, 2])
        df6 = make_df('BCD', [3, 4])
        print(df5); print(df6); print(pd.concat([df5, df6])
```

```
df5                 df6                pd.concat([df5, df6])
     A   B   C           B   C   D          A   B   C    D
 1  A1  B1  C1      3   B3  C3  D3     1    A1  B1  C1  NaN
 2  A2  B2  C2      4   B4  C4  D4     2    A2  B2  C2  NaN
                                       3   NaN  B3  C3   D3
                                       4   NaN  B4  C4   D4
```

By default, the entries for which no data is available are filled with NA values. To change this, we can specify one of several options for the join and join_axes parameters of the concatenate function. By default, the join is a union of the input columns (join='outer'), but we can change this to an intersection of the columns using join='inner':

```
In[14]: print(df5); print(df6);
        print(pd.concat([df5, df6], join='inner'))
```

```
df5                 df6                pd.concat([df5, df6], join='inner')
     A   B   C           B   C   D          B   C
 1  A1  B1  C1      3   B3  C3  D3     1   B1  C1
 2  A2  B2  C2      4   B4  C4  D4     2   B2  C2
                                       3   B3  C3
                                       4   B4  C4
```

Another option is to directly specify the index of the remaining colums using the join_axes argument, which takes a list of index objects. Here we'll specify that the returned columns should be the same as those of the first input:

```
In[15]: print(df5); print(df6);
        print(pd.concat([df5, df6], join_axes=[df5.columns]))
```

```
df5                 df6                pd.concat([df5, df6], join_axes=[df5.columns])
     A   B   C           B   C   D          A   B   C
 1  A1  B1  C1      3   B3  C3  D3     1    A1  B1  C1
 2  A2  B2  C2      4   B4  C4  D4     2    A2  B2  C2
```

```
3  NaN  B3  C3
4  NaN  B4  C4
```

The combination of options of the `pd.concat` function allows a wide range of possible behaviors when you are joining two datasets; keep these in mind as you use these tools for your own data.

The append() method

Because direct array concatenation is so common, `Series` and `DataFrame` objects have an `append` method that can accomplish the same thing in fewer keystrokes. For example, rather than calling `pd.concat([df1, df2])`, you can simply call `df1.append(df2)`:

```
In[16]: print(df1); print(df2); print(df1.append(df2))
```

```
df1            df2            df1.append(df2)
    A   B          A   B           A   B
 1  A1  B1      3  A3  B3      1   A1  B1
 2  A2  B2      4  A4  B4      2   A2  B2
                               3   A3  B3
                               4   A4  B4
```

Keep in mind that unlike the `append()` and `extend()` methods of Python lists, the `append()` method in Pandas does not modify the original object—instead, it creates a new object with the combined data. It also is not a very efficient method, because it involves creation of a new index *and* data buffer. Thus, if you plan to do multiple `append` operations, it is generally better to build a list of `DataFrame`s and pass them all at once to the `concat()` function.

In the next section, we'll look at another more powerful approach to combining data from multiple sources, the database-style merges/joins implemented in `pd.merge`. For more information on `concat()`, `append()`, and related functionality, see the "Merge, Join, and Concatenate" section of the Pandas documentation.

Combining Datasets: Merge and Join

One essential feature offered by Pandas is its high-performance, in-memory join and merge operations. If you have ever worked with databases, you should be familiar with this type of data interaction. The main interface for this is the `pd.merge` function, and we'll see a few examples of how this can work in practice.

Relational Algebra

The behavior implemented in `pd.merge()` is a subset of what is known as *relational algebra*, which is a formal set of rules for manipulating relational data, and forms the conceptual foundation of operations available in most databases. The strength of the relational algebra approach is that it proposes several primitive operations, which become the building blocks of more complicated operations on any dataset. With this lexicon of fundamental operations implemented efficiently in a database or other program, a wide range of fairly complicated composite operations can be performed.

Pandas implements several of these fundamental building blocks in the `pd.merge()` function and the related `join()` method of `Series` and `DataFrames`. As we will see, these let you efficiently link data from different sources.

Categories of Joins

The `pd.merge()` function implements a number of types of joins: the *one-to-one*, *many-to-one*, and *many-to-many* joins. All three types of joins are accessed via an identical call to the `pd.merge()` interface; the type of join performed depends on the form of the input data. Here we will show simple examples of the three types of merges, and discuss detailed options further below.

One-to-one joins

Perhaps the simplest type of merge expression is the one-to-one join, which is in many ways very similar to the column-wise concatenation seen in "Combining Datasets: Concat and Append" on page 141. As a concrete example, consider the following two `DataFrames`, which contain information on several employees in a company:

```
In[2]:
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering', 'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                    'hire_date': [2004, 2008, 2012, 2014]})
print(df1); print(df2)
```

```
df1                          df2
  employee        group        employee  hire_date
0      Bob   Accounting    0     Lisa       2004
1     Jake  Engineering    1      Bob       2008
2     Lisa  Engineering    2     Jake       2012
3      Sue           HR    3      Sue       2014
```

To combine this information into a single `DataFrame`, we can use the `pd.merge()` function:

```
In[3]: df3 = pd.merge(df1, df2)
       df3
```

```
Out[3]:   employee        group  hire_date
        0      Bob   Accounting       2008
        1     Jake  Engineering       2012
        2     Lisa  Engineering       2004
        3      Sue           HR       2014
```

The pd.merge() function recognizes that each DataFrame has an "employee" column, and automatically joins using this column as a key. The result of the merge is a new DataFrame that combines the information from the two inputs. Notice that the order of entries in each column is not necessarily maintained: in this case, the order of the "employee" column differs between df1 and df2, and the pd.merge() function correctly accounts for this. Additionally, keep in mind that the merge in general discards the index, except in the special case of merges by index (see "The left_index and right_index keywords" on page 151).

Many-to-one joins

Many-to-one joins are joins in which one of the two key columns contains duplicate entries. For the many-to-one case, the resulting DataFrame will preserve those duplicate entries as appropriate. Consider the following example of a many-to-one join:

```
In[4]: df4 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'],
                           'supervisor': ['Carly', 'Guido', 'Steve']})
       print(df3); print(df4); print(pd.merge(df3, df4))
```

```
df3                                   df4
  employee        group  hire_date           group supervisor
0      Bob   Accounting       2008    0   Accounting      Carly
1     Jake  Engineering       2012    1  Engineering      Guido
2     Lisa  Engineering       2004    2           HR      Steve
3      Sue           HR       2014

pd.merge(df3, df4)
  employee        group  hire_date supervisor
0      Bob   Accounting       2008      Carly
1     Jake  Engineering       2012      Guido
2     Lisa  Engineering       2004      Guido
3      Sue           HR       2014      Steve
```

The resulting DataFrame has an additional column with the "supervisor" information, where the information is repeated in one or more locations as required by the inputs.

Many-to-many joins

Many-to-many joins are a bit confusing conceptually, but are nevertheless well defined. If the key column in both the left and right array contains duplicates, then the result is a many-to-many merge. This will be perhaps most clear with a concrete example. Consider the following, where we have a DataFrame showing one or more skills associated with a particular group.

By performing a many-to-many join, we can recover the skills associated with any individual person:

```
In[5]: df5 = pd.DataFrame({'group': ['Accounting', 'Accounting',
                                     'Engineering', 'Engineering', 'HR', 'HR'],
```

```
                             'skills': ['math', 'spreadsheets', 'coding', 'linux',
                                        'spreadsheets', 'organization']})
print(df1); print(df5); print(pd.merge(df1, df5))
```

```
df1                            df5
  employee        group                   group        skills
0      Bob   Accounting        0   Accounting          math
1     Jake  Engineering        1   Accounting  spreadsheets
2     Lisa  Engineering        2  Engineering        coding
3      Sue           HR        3  Engineering         linux
                               4           HR  spreadsheets
                               5           HR  organization


pd.merge(df1, df5)
  employee        group        skills
0      Bob   Accounting          math
1      Bob   Accounting  spreadsheets
2     Jake  Engineering        coding
3     Jake  Engineering         linux
4     Lisa  Engineering        coding
5     Lisa  Engineering         linux
6      Sue           HR  spreadsheets
7      Sue           HR  organization
```

These three types of joins can be used with other Pandas tools to implement a wide array of functionality. But in practice, datasets are rarely as clean as the one we're working with here. In the following section, we'll consider some of the options provided by `pd.merge()` that enable you to tune how the join operations work.

Specification of the Merge Key

We've already seen the default behavior of `pd.merge()`: it looks for one or more matching column names between the two inputs, and uses this as the key. However, often the column names will not match so nicely, and `pd.merge()` provides a variety of options for handling this.

The on keyword

Most simply, you can explicitly specify the name of the key column using the `on` keyword, which takes a column name or a list of column names:

```
In[6]: print(df1); print(df2); print(pd.merge(df1, df2, on='employee'))
```

```
df1                            df2
  employee        group          employee  hire_date
0      Bob   Accounting          0     Lisa       2004
1     Jake  Engineering          1      Bob       2008
2     Lisa  Engineering          2     Jake       2012
3      Sue           HR          3      Sue       2014
```

```
pd.merge(df1, df2, on='employee')
  employee        group  hire_date
0      Bob   Accounting       2008
1     Jake  Engineering       2012
2     Lisa  Engineering       2004
3      Sue           HR       2014
```

This option works only if both the left and right `DataFrame`s have the specified column name.

The left_on and right_on keywords

At times you may wish to merge two datasets with different column names; for example, we may have a dataset in which the employee name is labeled as "name" rather than "employee". In this case, we can use the `left_on` and `right_on` keywords to specify the two column names:

```
In[7]:
df3 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'salary': [70000, 80000, 120000, 90000]})
print(df1); print(df3);
print(pd.merge(df1, df3, left_on="employee", right_on="name"))
```

```
df1                             df3
  employee        group            name  salary
0      Bob   Accounting          0   Bob   70000
1     Jake  Engineering          1  Jake   80000
2     Lisa  Engineering          2  Lisa  120000
3      Sue           HR          3   Sue   90000


pd.merge(df1, df3, left_on="employee", right_on="name")
  employee        group  name  salary
0      Bob   Accounting   Bob   70000
1     Jake  Engineering  Jake   80000
2     Lisa  Engineering  Lisa  120000
3      Sue           HR   Sue   90000
```

The result has a redundant column that we can drop if desired—for example, by using the `drop()` method of `DataFrame`s:

```
In[8]:
pd.merge(df1, df3, left_on="employee", right_on="name").drop('name', axis=1)
```

```
Out[8]:   employee        group  salary
        0      Bob   Accounting   70000
        1     Jake  Engineering   80000
        2     Lisa  Engineering  120000
        3      Sue           HR   90000
```

The left_index and right_index keywords

Sometimes, rather than merging on a column, you would instead like to merge on an index. For example, your data might look like this:

```
In[9]: df1a = df1.set_index('employee')
       df2a = df2.set_index('employee')
       print(df1a); print(df2a)
```

```
df1a                        df2a
                group                 hire_date
employee                     employee
Bob        Accounting        Lisa          2004
Jake      Engineering        Bob           2008
Lisa      Engineering        Jake          2012
Sue                HR        Sue           2014
```

You can use the index as the key for merging by specifying the `left_index` and/or `right_index` flags in `pd.merge()`:

```
In[10]:
print(df1a); print(df2a);
print(pd.merge(df1a, df2a, left_index=True, right_index=True))
```

```
df1a                        df2a
                group                 hire_date
employee                     employee
Bob        Accounting        Lisa          2004
Jake      Engineering        Bob           2008
Lisa      Engineering        Jake          2012
Sue                HR        Sue           2014

pd.merge(df1a, df2a, left_index=True, right_index=True)
                 group  hire_date
employee
Lisa      Engineering       2004
Bob        Accounting       2008
Jake      Engineering       2012
Sue                HR       2014
```

For convenience, `DataFrames` implement the `join()` method, which performs a merge that defaults to joining on indices:

```
In[11]: print(df1a); print(df2a); print(df1a.join(df2a))
```

```
df1a                      df2a
                group               hire_date
employee                   employee
Bob        Accounting      Lisa          2004
Jake      Engineering      Bob           2008
Lisa      Engineering      Jake          2012
Sue                HR      Sue           2014
```

```
df1a.join(df2a)
                group  hire_date
employee
Bob         Accounting       2008
Jake       Engineering       2012
Lisa       Engineering       2004
Sue                 HR       2014
```

If you'd like to mix indices and columns, you can combine `left_index` with `right_on` or `left_on` with `right_index` to get the desired behavior:

```
In[12]:
print(df1a); print(df3);
print(pd.merge(df1a, df3, left_index=True, right_on='name'))
```

```
df1a                        df3
                group
employee                    name  salary
Bob         Accounting    0   Bob   70000
Jake       Engineering    1  Jake   80000
Lisa       Engineering    2  Lisa  120000
Sue                 HR    3   Sue   90000

pd.merge(df1a, df3, left_index=True, right_on='name')
         group  name  salary
0   Accounting   Bob   70000
1  Engineering  Jake   80000
2  Engineering  Lisa  120000
3           HR   Sue   90000
```

All of these options also work with multiple indices and/or multiple columns; the interface for this behavior is very intuitive. For more information on this, see the "Merge, Join, and Concatenate" section of the Pandas documentation.

Specifying Set Arithmetic for Joins

In all the preceding examples we have glossed over one important consideration in performing a join: the type of set arithmetic used in the join. This comes up when a value appears in one key column but not the other. Consider this example:

```
In[13]: df6 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                            'food': ['fish', 'beans', 'bread']},
                           columns=['name', 'food'])
        df7 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                            'drink': ['wine', 'beer']},
                           columns=['name', 'drink'])
        print(df6); print(df7); print(pd.merge(df6, df7))
```

```
df6                 df7                 pd.merge(df6, df7)
    name   food         name drink          name   food  drink
0  Peter   fish     0    Mary  wine     0   Mary  bread   wine
1   Paul  beans     1  Joseph  beer
2   Mary  bread
```

Here we have merged two datasets that have only a single "name" entry in common: Mary. By default, the result contains the *intersection* of the two sets of inputs; this is what is known as an *inner join*. We can specify this explicitly using the `how` keyword, which defaults to `'inner'`:

```
In[14]: pd.merge(df6, df7, how='inner')
```

```
Out[14]:    name   food drink
         0  Mary  bread  wine
```

Other options for the `how` keyword are `'outer'`, `'left'`, and `'right'`. An *outer join* returns a join over the union of the input columns, and fills in all missing values with NAs:

```
In[15]: print(df6); print(df7); print(pd.merge(df6, df7, how='outer'))
```

```
df6                 df7                 pd.merge(df6, df7, how='outer')
     name   food         name drink          name   food drink
0  Peter   fish     0    Mary  wine     0   Peter   fish   NaN
1   Paul  beans     1  Joseph  beer     1    Paul  beans   NaN
2   Mary  bread                         2    Mary  bread  wine
                                        3  Joseph    NaN  beer
```

The *left join* and *right join* return join over the left entries and right entries, respectively. For example:

```
In[16]: print(df6); print(df7); print(pd.merge(df6, df7, how='left'))
```

```
df6                 df7                 pd.merge(df6, df7, how='left')
     name   food         name drink          name   food drink
0  Peter   fish     0    Mary  wine     0   Peter   fish   NaN
1   Paul  beans     1  Joseph  beer     1    Paul  beans   NaN
2   Mary  bread                         2    Mary  bread  wine
```

The output rows now correspond to the entries in the left input. Using `how='right'` works in a similar manner.

All of these options can be applied straightforwardly to any of the preceding join types.

Overlapping Column Names: The suffixes Keyword

Finally, you may end up in a case where your two input `DataFrame`s have conflicting column names. Consider this example:

```
In[17]: df8 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                            'rank': [1, 2, 3, 4]})
```

```
df9 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'rank': [3, 1, 4, 2]})
print(df8); print(df9); print(pd.merge(df8, df9, on="name"))
```

```
df8                 df9                 pd.merge(df8, df9, on="name")
    name  rank          name  rank          name  rank_x  rank_y
0    Bob     1      0    Bob     3      0    Bob       1       3
1   Jake     2      1   Jake     1      1   Jake       2       1
2   Lisa     3      2   Lisa     4      2   Lisa       3       4
3    Sue     4      3    Sue     2      3    Sue       4       2
```

Because the output would have two conflicting column names, the merge function automatically appends a suffix `_x` or `_y` to make the output columns unique. If these defaults are inappropriate, it is possible to specify a custom suffix using the `suffixes` keyword:

```
In[18]:
print(df8); print(df9);
print(pd.merge(df8, df9, on="name", suffixes=["_L", "_R"]))
```

```
df8                 df9
    name  rank          name  rank
0    Bob     1      0    Bob     3
1   Jake     2      1   Jake     1
2   Lisa     3      2   Lisa     4
3    Sue     4      3    Sue     2


pd.merge(df8, df9, on="name", suffixes=["_L", "_R"])
   name  rank_L  rank_R
0   Bob       1       3
1  Jake       2       1
2  Lisa       3       4
3   Sue       4       2
```

These suffixes work in any of the possible join patterns, and work also if there are multiple overlapping columns.

For more information on these patterns, see "Aggregation and Grouping" on page 158, where we dive a bit deeper into relational algebra. Also see the "Merge, Join, and Concatenate" section of the Pandas documentation for further discussion of these topics.

Example: US States Data

Merge and join operations come up most often when one is combining data from different sources. Here we will consider an example of some data about US states and their populations. The data files can be found at *http://github.com/jakevdp/data-USstates/*:

```
In[19]:
# Following are shell commands to download the data
```

```
# !curl -O https://raw.githubusercontent.com/jakevdp/
#    data-USstates/master/state-population.csv
# !curl -O https://raw.githubusercontent.com/jakevdp/
#    data-USstates/master/state-areas.csv
# !curl -O https://raw.githubusercontent.com/jakevdp/
#    data-USstates/master/state-abbrevs.csv
```

Let's take a look at the three datasets, using the Pandas `read_csv()` function:

```
In[20]: pop = pd.read_csv('state-population.csv')
        areas = pd.read_csv('state-areas.csv')
        abbrevs = pd.read_csv('state-abbrevs.csv')

        print(pop.head()); print(areas.head()); print(abbrevs.head())
```

```
pop.head()                                              areas.head()
  state/region     ages  year  population                    state  area (sq. mi)
0           AL  under18  2012   1117489.0               0     Alabama          52423
1           AL    total  2012   4817528.0               1      Alaska         656425
2           AL  under18  2010   1130966.0               2     Arizona         114006
3           AL    total  2010   4785570.0               3    Arkansas          53182
4           AL  under18  2011   1125763.0               3    Arkansas          53182
                                                        4  California         163707

abbrevs.head()
        state abbreviation
0     Alabama           AL
1      Alaska           AK
2     Arizona           AZ
3    Arkansas           AR
4  California           CA
```

Given this information, say we want to compute a relatively straightforward result: rank US states and territories by their 2010 population density. We clearly have the data here to find this result, but we'll have to combine the datasets to get it.

We'll start with a many-to-one merge that will give us the full state name within the population `DataFrame`. We want to merge based on the `state/region` column of `pop`, and the `abbreviation` column of `abbrevs`. We'll use `how='outer'` to make sure no data is thrown away due to mismatched labels.

```
In[21]: merged = pd.merge(pop, abbrevs, how='outer',
                          left_on='state/region', right_on='abbreviation')
        merged = merged.drop('abbreviation', 1) # drop duplicate info
        merged.head()
```

```
Out[21]:   state/region     ages  year  population    state
         0           AL  under18  2012   1117489.0  Alabama
         1           AL    total  2012   4817528.0  Alabama
         2           AL  under18  2010   1130966.0  Alabama
         3           AL    total  2010   4785570.0  Alabama
         4           AL  under18  2011   1125763.0  Alabama
```

Let's double-check whether there were any mismatches here, which we can do by looking for rows with nulls:

```
In[22]: merged.isnull().any()
```

```
Out[22]: state/region    False
         ages            False
         year            False
         population       True
         state            True
         dtype: bool
```

Some of the `population` info is null; let's figure out which these are!

```
In[23]: merged[merged['population'].isnull()].head()
```

```
Out[23]:      state/region     ages  year  population state
         2448           PR  under18  1990         NaN   NaN
         2449           PR    total  1990         NaN   NaN
         2450           PR    total  1991         NaN   NaN
         2451           PR  under18  1991         NaN   NaN
         2452           PR    total  1993         NaN   NaN
```

It appears that all the null population values are from Puerto Rico prior to the year 2000; this is likely due to this data not being available from the original source.

More importantly, we see also that some of the new `state` entries are also null, which means that there was no corresponding entry in the `abbrevs` key! Let's figure out which regions lack this match:

```
In[24]: merged.loc[merged['state'].isnull(), 'state/region'].unique()
```

```
Out[24]: array(['PR', 'USA'], dtype=object)
```

We can quickly infer the issue: our population data includes entries for Puerto Rico (PR) and the United States as a whole (USA), while these entries do not appear in the state abbreviation key. We can fix these quickly by filling in appropriate entries:

```
In[25]: merged.loc[merged['state/region'] == 'PR', 'state'] = 'Puerto Rico'
        merged.loc[merged['state/region'] == 'USA', 'state'] = 'United States'
        merged.isnull().any()
```

```
Out[25]: state/region    False
         ages            False
         year            False
         population       True
         state           False
         dtype: bool
```

No more nulls in the `state` column: we're all set!

Now we can merge the result with the area data using a similar procedure. Examining our results, we will want to join on the `state` column in both:

```
In[26]: final = pd.merge(merged, areas, on='state', how='left')
        final.head()
```

```
Out[26]:   state/region     ages  year  population    state  area (sq. mi)
        0            AL  under18  2012   1117489.0  Alabama        52423.0
        1            AL    total  2012   4817528.0  Alabama        52423.0
        2            AL  under18  2010   1130966.0  Alabama        52423.0
        3            AL    total  2010   4785570.0  Alabama        52423.0
        4            AL  under18  2011   1125763.0  Alabama        52423.0
```

Again, let's check for nulls to see if there were any mismatches:

```
In[27]: final.isnull().any()
```

```
Out[27]: state/region     False
         ages             False
         year             False
         population        True
         state            False
         area (sq. mi)     True
         dtype: bool
```

There are nulls in the `area` column; we can take a look to see which regions were ignored here:

```
In[28]: final['state'][final['area (sq. mi)'].isnull()].unique()
```

```
Out[28]: array(['United States'], dtype=object)
```

We see that our `areas` `DataFrame` does not contain the area of the United States as a whole. We could insert the appropriate value (using the sum of all state areas, for instance), but in this case we'll just drop the null values because the population density of the entire United States is not relevant to our current discussion:

```
In[29]: final.dropna(inplace=True)
        final.head()
```

```
Out[29]:   state/region     ages  year  population    state  area (sq. mi)
        0            AL  under18  2012   1117489.0  Alabama        52423.0
        1            AL    total  2012   4817528.0  Alabama        52423.0
        2            AL  under18  2010   1130966.0  Alabama        52423.0
        3            AL    total  2010   4785570.0  Alabama        52423.0
        4            AL  under18  2011   1125763.0  Alabama        52423.0
```

Now we have all the data we need. To answer the question of interest, let's first select the portion of the data corresponding with the year 2000, and the total population. We'll use the `query()` function to do this quickly (this requires the `numexpr` package to be installed; see "High-Performance Pandas: eval() and query()" on page 208):

```
In[30]: data2010 = final.query("year == 2010 & ages == 'total'")
        data2010.head()
```

```
Out[30]:     state/region   ages  year  population      state  area (sq. mi)
        3              AL  total  2010   4785570.0    Alabama        52423.0
        91             AK  total  2010    713868.0     Alaska       656425.0
```

```
101           AZ  total  2010   6408790.0     Arizona       114006.0
189           AR  total  2010   2922280.0    Arkansas        53182.0
197           CA  total  2010  37333601.0  California       163707.0
```

Now let's compute the population density and display it in order. We'll start by reindexing our data on the state, and then compute the result:

```
In[31]: data2010.set_index('state', inplace=True)
        density = data2010['population'] / data2010['area (sq. mi)']
```

```
In[32]: density.sort_values(ascending=False, inplace=True)
        density.head()
```

```
Out[32]: state
         District of Columbia    8898.897059
         Puerto Rico             1058.665149
         New Jersey              1009.253268
         Rhode Island             681.339159
         Connecticut              645.600649
         dtype: float64
```

The result is a ranking of US states plus Washington, DC, and Puerto Rico in order of their 2010 population density, in residents per square mile. We can see that by far the densest region in this dataset is Washington, DC (i.e., the District of Columbia); among states, the densest is New Jersey.

We can also check the end of the list:

```
In[33]: density.tail()
```

```
Out[33]: state
         South Dakota    10.583512
         North Dakota     9.537565
         Montana          6.736171
         Wyoming          5.768079
         Alaska           1.087509
         dtype: float64
```

We see that the least dense state, by far, is Alaska, averaging slightly over one resident per square mile.

This type of messy data merging is a common task when one is trying to answer questions using real-world data sources. I hope that this example has given you an idea of the ways you can combine tools we've covered in order to gain insight from your data!

Aggregation and Grouping

An essential piece of analysis of large data is efficient summarization: computing aggregations like `sum()`, `mean()`, `median()`, `min()`, and `max()`, in which a single number gives insight into the nature of a potentially large dataset. In this section, we'll explore aggregations in Pandas, from simple operations akin to what we've seen on NumPy arrays, to more sophisticated operations based on the concept of a `groupby`.

Planets Data

Here we will use the Planets dataset, available via the Seaborn package (see "Visualization with Seaborn" on page 311). It gives information on planets that astronomers have discovered around other stars (known as *extrasolar planets* or *exoplanets* for short). It can be downloaded with a simple Seaborn command:

```
In[2]: import seaborn as sns
       planets = sns.load_dataset('planets')
       planets.shape

Out[2]: (1035, 6)

In[3]: planets.head()

Out[3]:    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
```

This has some details on the 1,000+ exoplanets discovered up to 2014.

Simple Aggregation in Pandas

Earlier we explored some of the data aggregations available for NumPy arrays ("Aggregations: Min, Max, and Everything in Between" on page 58). As with a one-dimensional NumPy array, for a Pandas `Series` the aggregates return a single value:

```
In[4]: rng = np.random.RandomState(42)
       ser = pd.Series(rng.rand(5))
       ser

Out[4]: 0    0.374540
        1    0.950714
        2    0.731994
        3    0.598658
        4    0.156019
        dtype: float64

In[5]: ser.sum()

Out[5]: 2.8119254917081569

In[6]: ser.mean()

Out[6]: 0.56238509834163142
```

For a `DataFrame`, by default the aggregates return results within each column:

```
In[7]: df = pd.DataFrame({'A': rng.rand(5),
                          'B': rng.rand(5)})
       df
```

```
Out[7]:          A         B
        0  0.155995  0.020584
        1  0.058084  0.969910
        2  0.866176  0.832443
        3  0.601115  0.212339
        4  0.708073  0.181825
```

```
In[8]: df.mean()
```

```
Out[8]: A    0.477888
        B    0.443420
        dtype: float64
```

By specifying the `axis` argument, you can instead aggregate within each row:

```
In[9]: df.mean(axis='columns')
```

```
Out[9]: 0    0.088290
        1    0.513997
        2    0.849309
        3    0.406727
        4    0.444949
        dtype: float64
```

Pandas `Series` and `DataFrame`s include all of the common aggregates mentioned in "Aggregations: Min, Max, and Everything in Between" on page 58; in addition, there is a convenience method `describe()` that computes several common aggregates for each column and returns the result. Let's use this on the Planets data, for now dropping rows with missing values:

```
In[10]: planets.dropna().describe()
```

```
Out[10]:           number  orbital_period        mass    distance         year
         count  498.00000      498.000000  498.000000  498.000000   498.000000
         mean     1.73494      835.778671    2.509320   52.068213  2007.377510
         std      1.17572     1469.128259    3.636274   46.596041     4.167284
         min      1.00000        1.328300    0.003600    1.350000  1989.000000
         25%      1.00000       38.272250    0.212500   24.497500  2005.000000
         50%      1.00000      357.000000    1.245000   39.940000  2009.000000
         75%      2.00000      999.600000    2.867500   59.332500  2011.000000
         max      6.00000    17337.500000   25.000000  354.000000  2014.000000
```

This can be a useful way to begin understanding the overall properties of a dataset. For example, we see in the `year` column that although exoplanets were discovered as far back as 1989, half of all known exoplanets were not discovered until 2010 or after. This is largely thanks to the *Kepler* mission, which is a space-based telescope specifically designed for finding eclipsing planets around other stars.

Table 3-3 summarizes some other built-in Pandas aggregations.

Table 3-3. Listing of Pandas aggregation methods

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
`prod()`	Product of all items
`sum()`	Sum of all items

These are all methods of `DataFrame` and `Series` objects.

To go deeper into the data, however, simple aggregates are often not enough. The next level of data summarization is the `groupby` operation, which allows you to quickly and efficiently compute aggregates on subsets of data.

GroupBy: Split, Apply, Combine

Simple aggregations can give you a flavor of your dataset, but often we would prefer to aggregate conditionally on some label or index: this is implemented in the so-called `groupby` operation. The name "group by" comes from a command in the SQL database language, but it is perhaps more illuminative to think of it in the terms first coined by Hadley Wickham of Rstats fame: *split, apply, combine*.

Split, apply, combine

A canonical example of this split-apply-combine operation, where the "apply" is a summation aggregation, is illustrated in Figure 3-1.

Figure 3-1 makes clear what the `GroupBy` accomplishes:

- The *split* step involves breaking up and grouping a `DataFrame` depending on the value of the specified key.
- The *apply* step involves computing some function, usually an aggregate, transformation, or filtering, within the individual groups.
- The *combine* step merges the results of these operations into an output array.