Intro to data structures

We'll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, axis labeling, and alignment apply across all of the objects. To get started, import NumPy and load pandas into your namespace:

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

In [2]: import pandas as pd
```

Fundamentally, **data alignment is intrinsic**. The link between labels and data will not be broken unless done so explicitly by you.

We'll give a brief intro to the data structures, then consider all of the broad categories of functionality and methods in separate sections.

Series

`Series` is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the **index**. The basic method to create a `Series` is to call:

```
>>> s = pd.Series(data, index=index)
```

Here, `data` can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

The passed **index** is a list of axis labels. Thus, this separates into a few cases depending on what **data is**:

From ndarray

If `data` is an ndarray, **index** must be the same length as **data**. If no index is passed, one will be created having values `[0, ..., len(data) - 1]`.

```
In [3]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [4]: s
Out[4]:
a    0.469112
b   -0.282863
c   -1.509059
d   -1.135632
e    1.212112
dtype: float64

In [5]: s.index
Out[5]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [6]: pd.Series(np.random.randn(5))
Out[6]:
0   -0.173215
1    0.119209
2   -1.044236
3   -0.861849
4   -2.104569
dtype: float64
```

> **Note**
>
> pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time.

From dict

`Series` can be instantiated from dicts:

```
In [7]: d = {"b": 1, "a": 0, "c": 2}

In [8]: pd.Series(d)
Out[8]:
b    1
a    0
c    2
dtype: int64
```

If an index is passed, the values in data corresponding to the labels in the index will be pulled out.

```
In [9]: d = {"a": 0.0, "b": 1.0, "c": 2.0}

In [10]: pd.Series(d)
Out[10]:
a    0.0
b    1.0
c    2.0
dtype: float64

In [11]: pd.Series(d, index=["b", "c", "d", "a"])
Out[11]:
b    1.0
c    2.0
d    NaN
a    0.0
dtype: float64
```

> **Note**
>
> NaN (not a number) is the standard missing data marker used in pandas.

From scalar value

If `data` is a scalar value, an index must be provided. The value will be repeated to match the length of **index**.

```
In [12]: pd.Series(5.0, index=["a", "b", "c", "d", "e"])
Out[12]:
a    5.0
b    5.0
c    5.0
d    5.0
e    5.0
dtype: float64
```

Series is ndarray-like

`Series` acts very similarly to a `ndarray` and is a valid argument to most NumPy functions. However, operations such as slicing will also slice the index.

```
In [13]: s[0]
Out[13]: 0.4691122999071863

In [14]: s[:3]
Out[14]:
a    0.469112
b   -0.282863
c   -1.509059
dtype: float64

In [15]: s[s > s.median()]
Out[15]:
a    0.469112
e    1.212112
dtype: float64

In [16]: s[[4, 3, 1]]
Out[16]:
e    1.212112
d   -1.135632
b   -0.282863
dtype: float64

In [17]: np.exp(s)
Out[17]:
a    1.598575
b    0.753623
c    0.221118
d    0.321219
e    3.360575
dtype: float64
```

Note

We will address array-based indexing like `s[[4, 3, 1]]` in section on indexing.

Like a NumPy array, a pandas `Series` has a single `dtype`.

```
In [18]: s.dtype
Out[18]: dtype('float64')
```

This is often a NumPy dtype. However, pandas and 3rd-party libraries extend NumPy's type system in a few places, in which case the dtype would be an `ExtensionDtype`. Some examples within pandas are categorical and integer_na. See basics.dtypes for more.

If you need the actual array backing a `Series`, use `Series.array`.

```
In [19]: s.array
Out[19]:
<PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124,
 -1.1356323710171934,  1.2121120250208506]
Length: 5, dtype: float64
```

Accessing the array can be useful when you need to do some operation without the index (to disable automatic alignment, for example).

`Series.array` will always be an `ExtensionArray`. Briefly, an ExtensionArray is a thin wrapper around one or more *concrete* arrays like a `numpy.ndarray`. pandas knows how to take an `ExtensionArray` and store it in a `Series` or a column of a `DataFrame`. See basics.dtypes for more.

While `Series` is ndarray-like, if you need an *actual* ndarray, then use `Series.to_numpy()`.

```
In [20]: s.to_numpy()
Out[20]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])
```

Even if the `Series` is backed by a `ExtensionArray`, `Series.to_numpy()` will return a NumPy ndarray.

Series is dict-like

A `Series` is also like a fixed-size dict in that you can get and set values by index label:

```
In [21]: s["a"]
Out[21]: 0.4691122999071863

In [22]: s["e"] = 12.0

In [23]: s
Out[23]:
a     0.469112
b    -0.282863
c    -1.509059
d    -1.135632
e    12.000000
dtype: float64

In [24]: "e" in s
Out[24]: True

In [25]: "f" in s
Out[25]: False
```

If a label is not contained in the index, an exception is raised:

```
In [26]: s["f"]
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
File ~/d01w23-team-timbits/deliverable4/pandas/pandas/core/indexes/base.py:3802, in Index.get_loc(self, key, method, tolerance)
   3801 try:
-> 3802     return self._engine.get_loc(casted_key)
   3803 except KeyError as err:

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/_libs/index.pyx:138, in pandas._libs.index.IndexEngine.get_loc()

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/_libs/index.pyx:165, in pandas._libs.index.IndexEngine.get_loc()

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/_libs/hashtable_class_helper.pxi:5745, in pandas._libs.hashtable.PyObjectHashTable.get_item()

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/_libs/hashtable_class_helper.pxi:5753, in pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: 'f'

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

KeyError                                  Traceback (most recent call last)
Cell In[26], line 1
----> 1 s["f"]

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/core/series.py:981, in Series.__getitem__(self, key)
    978     return self._values[key]
    980 elif key_is_scalar:
--> 981     return self._get_value(key)
    983 if is_hashable(key):
    984     # Otherwise index.get_value will raise InvalidIndexError
    985     try:
    986         # For labels that don't resolve as scalars like tuples and frozensets

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/core/series.py:1089, in Series._get_value(self, label, takeable)
   1086     return self._values[label]
   1088 # Similar to Index.get_value, but we do not fall back to positional
-> 1089 loc = self.index.get_loc(label)
   1090 return self.index._get_values_for_loc(self, loc, label)

File ~/d01w23-team-timbits/deliverable4/pandas/pandas/core/indexes/base.py:3804, in Index.get_loc(self, key, method, tolerance)
   3802     return self._engine.get_loc(casted_key)
   3803 except KeyError as err:
-> 3804     raise KeyError(key) from err
   3805 except TypeError:
   3806     # If we have a listlike key, _check_indexing_error will raise
   3807     #  InvalidIndexError. Otherwise we fall through and re-raise
   3808     #  the TypeError.
   3809     self._check_indexing_error(key)

KeyError: 'f'
```

Using the `Series.get()` method, a missing label will return None or specified default:

```
In [27]: s.get("f")

In [28]: s.get("f", np.nan)
Out[28]: nan
```

These labels can also be accessed by attribute.

Vectorized operations and label alignment with Series

When working with raw NumPy arrays, looping through value-by-value is usually not necessary. The same is true when working with `Series` in pandas. `Series` can also be passed into most NumPy methods expecting an ndarray.

```
In [29]: s + s
Out[29]:
a     0.938225
b    -0.565727
c    -3.018117
d    -2.271265
e    24.000000
dtype: float64

In [30]: s * 2
Out[30]:
a     0.938225
b    -0.565727
c    -3.018117
d    -2.271265
e    24.000000
dtype: float64

In [31]: np.exp(s)
Out[31]:
a         1.598575
b         0.753623
c         0.221118
d         0.321219
e    162754.791419
dtype: float64
```

A key difference between `Series` and ndarray is that operations between `Series` automatically align the data based on label. Thus, you can write computations without giving consideration to whether the `Series` involved have the same labels.

```
In [32]: s[1:] + s[:-1]
Out[32]:
a         NaN
b   -0.565727
c   -3.018117
d   -2.271265
e         NaN
dtype: float64
```

The result of an operation between unaligned `Series` will have the **union** of the indexes involved. If a label is not found in one `Series` or the other, the result will be marked as missing `NaN`. Being able to write code without doing any explicit data alignment grants immense freedom and flexibility in interactive data analysis and research. The integrated data alignment features of the pandas data structures set pandas apart from the majority of related tools for working with labeled data.

> **Note**
>
> In general, we chose to make the default result of operations between differently indexed objects yield the **union** of the indexes in order to avoid loss of information. Having an index label, though the data is missing, is typically important information as part of a computation. You of course have the option of dropping labels with missing data via the **dropna** function.

Name attribute

`Series` also has a `name` attribute:

```
In [33]: s = pd.Series(np.random.randn(5), name="something")

In [34]: s
Out[34]:
0   -0.494929
1    1.071804
2    0.721555
3   -0.706771
4   -1.039575
Name: something, dtype: float64

In [35]: s.name
Out[35]: 'something'
```

The `Series` `name` can be assigned automatically in many cases, in particular, when selecting a single column from a `DataFrame`, the `name` will be assigned the column label.

You can rename a `Series` with the `pandas.Series.rename()` method.

```
In [36]: s2 = s.rename("different")

In [37]: s2.name
Out[37]: 'different'
```

Note that `s` and `s2` refer to different objects.

DataFrame

`DataFrame` is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or `Series`
- 2-D numpy.ndarray
- Structured or record ndarray
- A `Series`
- Another `DataFrame`

Along with the data, you can optionally pass **index** (row labels) and **columns** (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

From dict of Series or dicts

The resulting **index** will be the **union** of the indexes of the various Series. If there are any nested dicts, these will first be converted to Series. If no columns are passed, the columns will be the ordered list of dict keys.

```
In [38]: d = {
   ....:     "one": pd.Series([1.0, 2.0, 3.0], index=["a", "b", "c"]),
   ....:     "two": pd.Series([1.0, 2.0, 3.0, 4.0], index=["a", "b", "c", "d"]),
   ....: }
   ....:

In [39]: df = pd.DataFrame(d)

In [40]: df
Out[40]:
   one  two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN  4.0

In [41]: pd.DataFrame(d, index=["d", "b", "a"])
Out[41]:
   one  two
d  NaN  4.0
b  2.0  2.0
a  1.0  1.0

In [42]: pd.DataFrame(d, index=["d", "b", "a"], columns=["two", "three"])
Out[42]:
   two three
d  4.0   NaN
b  2.0   NaN
a  1.0   NaN
```

The row and column labels can be accessed respectively by accessing the **index** and **columns** attributes:

> **Note**
>
> When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

```
In [43]: df.index
Out[43]: Index(['a', 'b', 'c', 'd'], dtype='object')

In [44]: df.columns
Out[44]: Index(['one', 'two'], dtype='object')
```

From dict of ndarrays / lists

The ndarrays must all be the same length. If an index is passed, it must also be the same length as the arrays. If no index is passed, the result will be `range(n)`, where `n` is the array length.

```
In [45]: d = {"one": [1.0, 2.0, 3.0, 4.0], "two": [4.0, 3.0, 2.0, 1.0]}

In [46]: pd.DataFrame(d)
Out[46]:
   one  two
0  1.0  4.0
1  2.0  3.0
2  3.0  2.0
3  4.0  1.0

In [47]: pd.DataFrame(d, index=["a", "b", "c", "d"])
Out[47]:
   one  two
a  1.0  4.0
b  2.0  3.0
c  3.0  2.0
d  4.0  1.0
```

From dfBuilder

This is a custom class that allows you to build a DataFrame row-wisely. The class is initialized with columns and an optional dtypes, which corresponds to the elements in a DataFrame . You can then append rows to the dfBuilder using the appendRow or appendDict methods. The dfBuilder can be converted to a DataFrame using the build() method.

```
>>>
In [48]: from pandas import dfBuilder

In [49]: builder = dfBuilder(columns = ["name", "age", "gender"], dtypes=[str, int, str])

In [50]: builder = builder.appendRow(["John", 19, 'M']).appendRow(["Mary", 20, 'F'])

In [51]: builder.build()
Out[51]:
   name  age gender
0  John   19      M
1  Mary   20      F
```

Note

Make sure the row data you provide has the same length with the columns you provide. Otherwise, an error will be raised.

You can choose to omit the dtypes argument in the initialization, in which case the dtypes will be inferred from the data. On the other hand, you can choose to add dtypes by using asType later on.

```
>>>
In [52]: builder = dfBuilder(columns = ["name", "age", "gender"])

In [53]: builder = builder.appendRow(["John", 19, 'M']).appendRow(["Mary", 20, 'F'])

In [54]: builder.build()
Out[54]:
   name  age gender
0  John   19      M
1  Mary   20      F

In [55]: builder.asType([str, int, str]).build()
Out[55]:
   name  age gender
0  John   19      M
1  Mary   20      F
```

Note

Make sure the data you provide is compatible to the dtypes you provide. Numpy will try to convert the data to the dtype you provide. If the conversion is not possible, an error will be raised.

```
>>>
In [56]: builder = dfBuilder(columns=["name", "age", "gender"])

In [57]: builder = builder.appendDict({"name": "Jason", "age": 20, "gender": "M"})

In [58]: builder.build()
Out[58]:
    name  age gender
0  Jason   20      M
```

Note

Make sure the dict data you provide has the keys with the columns names you provide. Otherwise, an error will be raised.

From structured or record array

This case is handled identically to a dict of arrays.

```
In [59]: data = np.zeros((2,), dtype=[("A", "i4"), ("B", "f4"), ("C", "a10")])

In [60]: data[:] = [(1, 2.0, "Hello"), (2, 3.0, "World")]

In [61]: pd.DataFrame(data)
Out[61]:
   A    B         C
0  1  2.0  b'Hello'
1  2  3.0  b'World'

In [62]: pd.DataFrame(data, index=["first", "second"])
Out[62]:
        A    B         C
first   1  2.0  b'Hello'
second  2  3.0  b'World'

In [63]: pd.DataFrame(data, columns=["C", "A", "B"])
Out[63]:
          C  A    B
0  b'Hello'  1  2.0
1  b'World'  2  3.0
```

Note

DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

From a list of dicts

```
In [64]: data2 = [{"a": 1, "b": 2}, {"a": 5, "b": 10, "c": 20}]

In [65]: pd.DataFrame(data2)
Out[65]:
   a   b     c
0  1   2   NaN
1  5  10  20.0

In [66]: pd.DataFrame(data2, index=["first", "second"])
Out[66]:
        a   b     c
first   1   2   NaN
second  5  10  20.0

In [67]: pd.DataFrame(data2, columns=["a", "b"])
Out[67]:
   a   b
0  1   2
1  5  10
```

From a dict of tuples

You can automatically create a MultiIndexed frame by passing a tuples dictionary.

```
In [68]: pd.DataFrame(
   ....:     {
   ....:         ("a", "b"): {("A", "B"): 1, ("A", "C"): 2},
   ....:         ("a", "a"): {("A", "C"): 3, ("A", "B"): 4},
   ....:         ("a", "c"): {("A", "B"): 5, ("A", "C"): 6},
   ....:         ("b", "a"): {("A", "C"): 7, ("A", "B"): 8},
   ....:         ("b", "b"): {("A", "D"): 9, ("A", "B"): 10},
   ....:     }
   ....: )
   ....:
Out[68]:
       a              b      
       b    a    c    a     b
A B  1.0  4.0  5.0  8.0  10.0
  C  2.0  3.0  6.0  7.0   NaN
  D  NaN  NaN  NaN  NaN   9.0
```

From a Series

The result will be a DataFrame with the same index as the input Series, and with one column whose name is the original name of the Series (only if no other column name provided).

```
In [69]: ser = pd.Series(range(3), index=list("abc"), name="ser")

In [70]: pd.DataFrame(ser)
Out[70]:
   ser
a    0
b    1
c    2
```

From a list of namedtuples

The field names of the first `namedtuple` in the list determine the columns of the `DataFrame`. The remaining namedtuples (or tuples) are simply unpacked and their values are fed into the rows of the `DataFrame`. If any of those tuples is shorter than the first `namedtuple` then the later columns in the corresponding row are marked as missing values. If any are longer than the first `namedtuple`, a `ValueError` is raised.

```
In [71]: from collections import namedtuple

In [72]: Point = namedtuple("Point", "x y")

In [73]: pd.DataFrame([Point(0, 0), Point(0, 3), (2, 3)])
Out[73]:
   x  y
0  0  0
1  0  3
2  2  3

In [74]: Point3D = namedtuple("Point3D", "x y z")

In [75]: pd.DataFrame([Point3D(0, 0, 0), Point3D(0, 3, 5), Point(2, 3)])
Out[75]:
   x  y    z
0  0  0  0.0
1  0  3  5.0
2  2  3  NaN
```

From a list of dataclasses

New in version 1.1.0.

Data Classes as introduced in PEP557, can be passed into the DataFrame constructor. Passing a list of dataclasses is equivalent to passing a list of dictionaries.

Please be aware, that all values in the list should be dataclasses, mixing types in the list would result in a `TypeError`.

```
In [76]: from dataclasses import make_dataclass

In [77]: Point = make_dataclass("Point", [("x", int), ("y", int)])

In [78]: pd.DataFrame([Point(0, 0), Point(0, 3), Point(2, 3)])
Out[78]:
   x  y
0  0  0
1  0  3
2  2  3
```

Missing data

To construct a DataFrame with missing data, we use `np.nan` to represent missing values. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing. See Missing data for more.

Alternate constructors

DataFrame.from_dict

`DataFrame.from_dict()` takes a dict of dicts or a dict of array-like sequences and returns a DataFrame. It operates like the `DataFrame` constructor except for the `orient` parameter which is `'columns'` by default, but which can be set to `'index'` in order to use the dict keys as row labels.

```
In [79]: pd.DataFrame.from_dict(dict([("A", [1, 2, 3]), ("B", [4, 5, 6])]))
Out[79]: 
   A  B
0  1  4
1  2  5
2  3  6
```

If you pass `orient='index'`, the keys will be the row labels. In this case, you can also pass the desired column names:

```
In [80]: pd.DataFrame.from_dict(
   ....:     dict([("A", [1, 2, 3]), ("B", [4, 5, 6])]),
   ....:     orient="index",
   ....:     columns=["one", "two", "three"],
   ....: )
   ....: 
Out[80]: 
   one  two  three
A    1    2      3
B    4    5      6
```

DataFrame.from_records

`DataFrame.from_records()` takes a list of tuples or an ndarray with structured dtype. It works analogously to the normal `DataFrame` constructor, except that the resulting DataFrame index may be a specific field of the structured dtype.

```
In [81]: data
Out[81]: 
array([(1, 2., b'Hello'), (2, 3., b'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])

In [82]: pd.DataFrame.from_records(data, index="C")
Out[82]: 
          A    B
C               
b'Hello'  1  2.0
b'World'  2  3.0
```

Column selection, addition, deletion

You can treat a `DataFrame` semantically like a dict of like-indexed `Series` objects. Getting, setting, and deleting columns works with the same syntax as the analogous dict operations:

```
In [83]: df["one"]
Out[83]: 
a    1.0
b    2.0
c    3.0
d    NaN
Name: one, dtype: float64

In [84]: df["three"] = df["one"] * df["two"]

In [85]: df["flag"] = df["one"] > 2

In [86]: df
Out[86]: 
   one  two  three   flag
a  1.0  1.0    1.0  False
b  2.0  2.0    4.0  False
c  3.0  3.0    9.0   True
d  NaN  4.0    NaN  False
```

Columns can be deleted or popped like with a dict:

```
In [87]: del df["two"]

In [88]: three = df.pop("three")

In [89]: df
Out[89]: 
   one   flag
a  1.0  False
b  2.0  False
c  3.0   True
d  NaN  False
```

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [90]: df["foo"] = "bar"

In [91]: df
Out[91]: 
   one   flag  foo
a  1.0  False  bar
b  2.0  False  bar
c  3.0   True  bar
d  NaN  False  bar
```

When inserting a `Series` that does not have the same index as the `DataFrame`, it will be conformed to the DataFrame's index:

```
In [92]: df["one_trunc"] = df["one"][:2]

In [93]: df
Out[93]: 
   one   flag  foo  one_trunc
a  1.0  False  bar        1.0
b  2.0  False  bar        2.0
c  3.0   True  bar        NaN
d  NaN  False  bar        NaN
```

You can insert raw ndarrays but their length must match the length of the DataFrame's index.

By default, columns get inserted at the end. `DataFrame.insert()` inserts at a particular location in the columns:

```
In [94]: df.insert(1, "bar", df["one"])

In [95]: df
Out[95]: 
   one  bar   flag  foo  one_trunc
a  1.0  1.0  False  bar        1.0
b  2.0  2.0  False  bar        2.0
c  3.0  3.0   True  bar        NaN
d  NaN  NaN  False  bar        NaN
```

Assigning new columns in method chains

Inspired by dplyr's `mutate` verb, DataFrame has an `assign()` method that allows you to easily create new columns that are potentially derived from existing columns.

```
In [96]: iris = pd.read_csv("data/iris.data")

In [97]: iris.head()
Out[97]: 
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name
0          5.1         3.5          1.4         0.2  Iris-setosa
1          4.9         3.0          1.4         0.2  Iris-setosa
2          4.7         3.2          1.3         0.2  Iris-setosa
3          4.6         3.1          1.5         0.2  Iris-setosa
4          5.0         3.6          1.4         0.2  Iris-setosa

In [98]: iris.assign(sepal_ratio=iris["SepalWidth"] / iris["SepalLength"]).head()
Out[98]: 
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa     0.686275
1          4.9         3.0          1.4         0.2  Iris-setosa     0.612245
2          4.7         3.2          1.3         0.2  Iris-setosa     0.680851
3          4.6         3.1          1.5         0.2  Iris-setosa     0.673913
4          5.0         3.6          1.4         0.2  Iris-setosa     0.720000
```

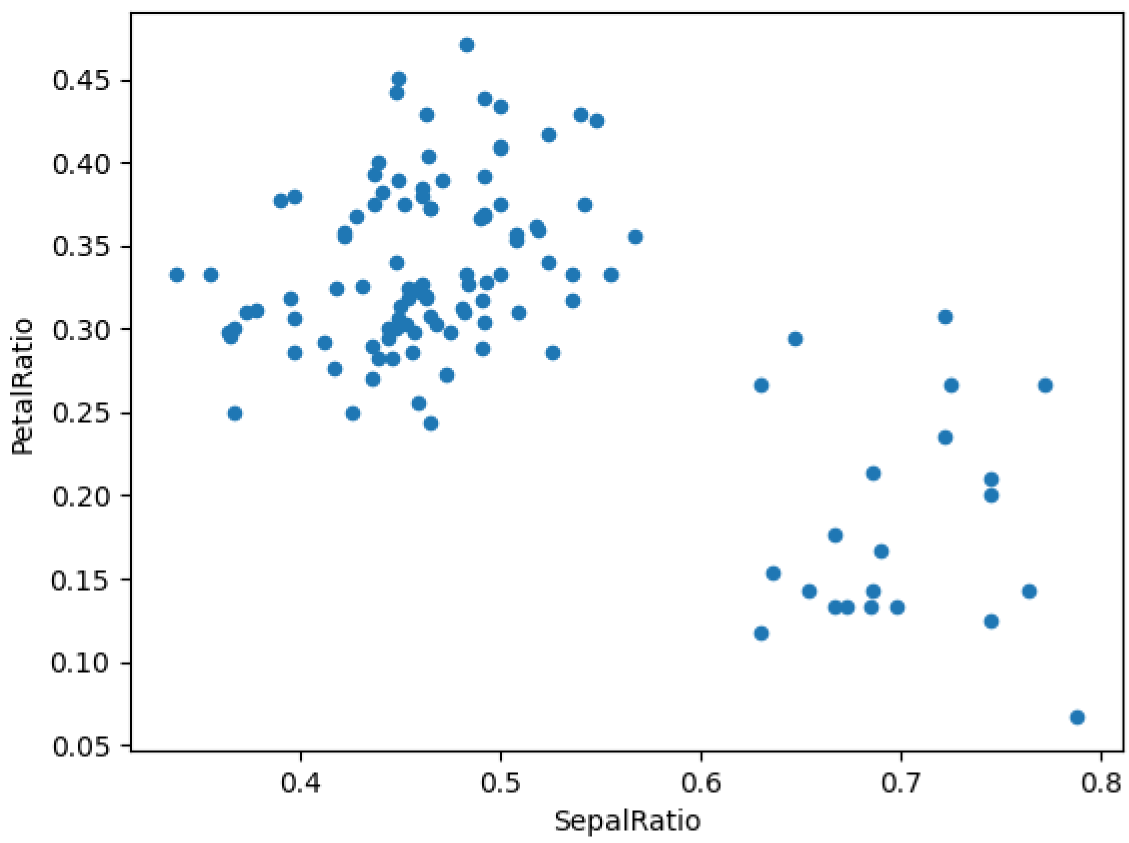
In the example above, we inserted a precomputed value. We can also pass in a function of one argument to be evaluated on the DataFrame being assigned to.

```
In [99]: iris.assign(sepal_ratio=lambda x: (x["SepalWidth"] / x["SepalLength"])).head()
Out[99]: 
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa     0.686275
1          4.9         3.0          1.4         0.2  Iris-setosa     0.612245
2          4.7         3.2          1.3         0.2  Iris-setosa     0.680851
3          4.6         3.1          1.5         0.2  Iris-setosa     0.673913
4          5.0         3.6          1.4         0.2  Iris-setosa     0.720000
```

`assign()` **always** returns a copy of the data, leaving the original DataFrame untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don't have a reference to the DataFrame at hand. This is common when using `assign()` in a chain of operations. For example, we can limit the DataFrame to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:

```
In [100]: (
   .....:     iris.query("SepalLength > 5")
   .....:     .assign(
   .....:         SepalRatio=lambda x: x.SepalWidth / x.SepalLength,
   .....:         PetalRatio=lambda x: x.PetalWidth / x.PetalLength,
   .....:     )
   .....:     .plot(kind="scatter", x="SepalRatio", y="PetalRatio")
   .....: )
   .....:
Out[100]: <AxesSubplot: xlabel='SepalRatio', ylabel='PetalRatio'>
```



Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that's been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn't have a reference to the *filtered* DataFrame available.

The function signature for `assign()` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. A *copy* of the original `DataFrame` is returned, with the new values inserted.

The order of `**kwargs` is preserved. This allows for *dependent* assignment, where an expression later in `**kwargs` can refer to a column created earlier in the same `assign()`.

```
In [101]: dfa = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})

In [102]: dfa.assign(C=lambda x: x["A"] + x["B"], D=lambda x: x["A"] + x["C"])
Out[102]:
   A  B  C   D
0  1  4  5   6
1  2  5  7   9
2  3  6  9  12
```

In the second expression, `x['C']` will refer to the newly created column, that's equal to `dfa['A'] + dfa['B']`.

Indexing / selection

The basics of indexing are as follows:

Operation	Syntax	Result
Select column	`df[col]`	Series

Operation	Syntax	Result
Select row by label	`df.loc[label]`	Series
Select row by integer location	`df.iloc[loc]`	Series
Slice rows	`df[5:10]`	DataFrame
Select rows by boolean vector	`df[bool_vec]`	DataFrame

Row selection, for example, returns a `Series` whose index is the columns of the `DataFrame`:

```
In [103]: df.loc["b"]
Out[103]:
one            2.0
bar            2.0
flag         False
foo            bar
one_trunc      2.0
Name: b, dtype: object

In [104]: df.iloc[2]
Out[104]:
one           3.0
bar           3.0
flag         True
foo           bar
one_trunc     NaN
Name: c, dtype: object
```

For a more exhaustive treatment of sophisticated label-based indexing and slicing, see the section on indexing. We will address the fundamentals of reindexing / conforming to new sets of labels in the section on reindexing.

Data alignment and arithmetic

Data alignment between `DataFrame` objects automatically align on **both the columns and the index (row labels)**. Again, the resulting object will have the union of the column and row labels.

```
In [105]: df = pd.DataFrame(np.random.randn(10, 4), columns=["A", "B", "C", "D"])

In [106]: df2 = pd.DataFrame(np.random.randn(7, 3), columns=["A", "B", "C"])

In [107]: df + df2
Out[107]:
          A         B         C   D
0  0.045691 -0.014138  1.380871 NaN
1 -0.955398 -1.501007  0.037181 NaN
2 -0.662690  1.534833 -0.859691 NaN
3 -2.452949  1.237274 -0.133712 NaN
4  1.414490  1.951676 -2.320422 NaN
5 -0.494922 -1.649727 -1.084601 NaN
6 -1.047551 -0.748572 -0.805479 NaN
7       NaN       NaN       NaN NaN
8       NaN       NaN       NaN NaN
9       NaN       NaN       NaN NaN
```

When doing an operation between `DataFrame` and `Series`, the default behavior is to align the `Series` **index** on the `DataFrame` **columns**, thus broadcasting row-wise. For example:

```
In [108]: df - df.iloc[0]
Out[108]:
          A         B         C         D
0  0.000000  0.000000  0.000000  0.000000
1 -1.359261 -0.248717 -0.453372 -1.754659
2  0.253128  0.829678  0.010026 -1.991234
3 -1.311128  0.054325 -1.724913 -1.620544
4  0.573025  1.500742 -0.676070  1.367331
5 -1.741248  0.781993 -1.241620 -2.053136
6 -1.240774 -0.869551 -0.153282  0.000430
7 -0.743894  0.411013 -0.929563 -0.282386
8 -1.194921  1.320690  0.238224 -1.482644
9  2.293786  1.856228  0.773289 -1.446531
```

For explicit control over the matching and broadcasting behavior, see the section on flexible binary operations.

Arithmetic operations with scalars operate element-wise:

```
In [109]: df * 5 + 2
Out[109]: 
           A         B         C          D
0   3.359299 -0.124862  4.835102   3.381160
1  -3.437003 -1.368449  2.568242  -5.392133
2   4.624938  4.023526  4.885230  -6.575010
3  -3.196342  0.146766 -3.789461  -4.721559
4   6.224426  7.378849  1.454750  10.217815
5  -5.346940  3.785103 -1.373001  -6.884519
6  -2.844569 -4.472618  4.068691   3.383309
7  -0.360173  1.930201  0.187285   1.969232
8  -2.615303  6.478587  6.026220  -4.032059
9  14.828230  9.156280  8.701544  -3.851494

In [110]: 1 / df
Out[110]: 
          A          B         C           D
0  3.678365  -2.353094  1.763605    3.620145
1 -0.919624  -1.484363  8.799067   -0.676395
2  1.904807   2.470934  1.732964   -0.583090
3 -0.962215  -2.697986 -0.863638   -0.743875
4  1.183593   0.929567 -9.170108    0.608434
5 -0.680555   2.800959 -1.482360   -0.562777
6 -1.032084  -0.772485  2.416988    3.614523
7 -2.118489 -71.634509 -2.758294 -162.507295
8 -1.083352   1.116424  1.241860   -0.828904
9  0.389765   0.698687  0.746097   -0.854483

In [111]: df ** 4
Out[111]: 
           A             B         C             D
0   0.005462  3.261689e-02  0.103370  5.822320e-03
1   1.398165  2.059869e-01  0.000167  4.777482e+00
2   0.075962  2.682596e-02  0.110877  8.650845e+00
3   1.166571  1.887302e-02  1.797515  3.265879e+00
4   0.509555  1.339298e+00  0.000141  7.297019e+00
5   4.661717  1.624699e-02  0.207103  9.969092e+00
6   0.881334  2.808277e+00  0.029302  5.858632e-03
7   0.049647  3.797614e-08  0.017276  1.433866e-09
8   0.725974  6.437005e-01  0.420446  2.118275e+00
9  43.329821  4.196326e+00  3.227153  1.875802e+00
```

Boolean operators operate element-wise as well:

```
In [112]: df1 = pd.DataFrame({"a": [1, 0, 1], "b": [0, 1, 1]}, dtype=bool)

In [113]: df2 = pd.DataFrame({"a": [0, 1, 1], "b": [1, 1, 0]}, dtype=bool)

In [114]: df1 & df2
Out[114]: 
       a      b
0  False  False
1  False   True
2   True  False

In [115]: df1 | df2
Out[115]: 
      a     b
0  True  True
1  True  True
2  True  True

In [116]: df1 ^ df2
Out[116]: 
       a      b
0   True   True
1   True  False
2  False   True

In [117]: -df1
Out[117]: 
       a      b
0  False   True
1   True  False
2  False  False
```

Transposing

To transpose, access the `T` attribute or `DataFrame.transpose()`, similar to an ndarray:

```
# only show the first 5 rows
In [118]: df[:5].T
Out[118]:
          0         1         2         3         4
A  0.271860 -1.087401  0.524988 -1.039268  0.844885
B -0.424972 -0.673690  0.404705 -0.370647  1.075770
C  0.567020  0.113648  0.577046 -1.157892 -0.109050
D  0.276232 -1.478427 -1.715002 -1.344312  1.643563
```

DataFrame interoperability with NumPy functions

Most NumPy functions can be called directly on `Series` and `DataFrame`.

```
In [119]: np.exp(df)
Out[119]:
           A         B         C         D
0   1.312403  0.653788  1.763006  1.318154
1   0.337092  0.509824  1.120358  0.227996
2   1.690438  1.498861  1.780770  0.179963
3   0.353713  0.690288  0.314148  0.260719
4   2.327710  2.932249  0.896686  5.173571
5   0.230066  1.429065  0.509360  0.169161
6   0.379495  0.274028  1.512461  1.318720
7   0.623732  0.986137  0.695904  0.993865
8   0.397301  2.449092  2.237242  0.299269
9  13.009059  4.183951  3.820223  0.310274

In [120]: np.asarray(df)
Out[120]:
array([[ 0.2719, -0.425 ,  0.567 ,  0.2762],
       [-1.0874, -0.6737,  0.1136, -1.4784],
       [ 0.525 ,  0.4047,  0.577 , -1.715 ],
       [-1.0393, -0.3706, -1.1579, -1.3443],
       [ 0.8449,  1.0758, -0.109 ,  1.6436],
       [-1.4694,  0.357 , -0.6746, -1.7769],
       [-0.9689, -1.2945,  0.4137,  0.2767],
       [-0.472 , -0.014 , -0.3625, -0.0062],
       [-0.9231,  0.8957,  0.8052, -1.2064],
       [ 2.5656,  1.4313,  1.3403, -1.1703]])
```

`DataFrame` is not intended to be a drop-in replacement for ndarray as its indexing semantics and data model are quite different in places from an n-dimensional array.

`Series` implements `__array_ufunc__`, which allows it to work with NumPy's universal functions.

The ufunc is applied to the underlying array in a `Series`.

```
In [121]: ser = pd.Series([1, 2, 3, 4])

In [122]: np.exp(ser)
Out[122]:
0     2.718282
1     7.389056
2    20.085537
3    54.598150
dtype: float64
```

> *Changed in version 0.25.0:* When multiple `Series` are passed to a ufunc, they are aligned before performing the operation.

Like other parts of the library, pandas will automatically align labeled inputs as part of a ufunc with multiple inputs. For example, using `numpy.remainder()` on two `Series` with differently ordered labels will align before the operation.

```
In [123]: ser1 = pd.Series([1, 2, 3], index=["a", "b", "c"])

In [124]: ser2 = pd.Series([1, 3, 5], index=["b", "a", "c"])

In [125]: ser1
Out[125]:
a    1
b    2
c    3
dtype: int64

In [126]: ser2
Out[126]:
b    1
a    3
c    5
dtype: int64

In [127]: np.remainder(ser1, ser2)
Out[127]:
a    1
b    0
c    3
dtype: int64
```

As usual, the union of the two indices is taken, and non-overlapping values are filled with missing values.

```
In [128]: ser3 = pd.Series([2, 4, 6], index=["b", "c", "d"])

In [129]: ser3
Out[129]:
b    2
c    4
d    6
dtype: int64

In [130]: np.remainder(ser1, ser3)
Out[130]:
a    NaN
b    0.0
c    3.0
d    NaN
dtype: float64
```

When a binary ufunc is applied to a `Series` and `Index`, the `Series` implementation takes precedence and a `Series` is returned.

```
In [131]: ser = pd.Series([1, 2, 3])

In [132]: idx = pd.Index([4, 5, 6])

In [133]: np.maximum(ser, idx)
Out[133]:
0    4
1    5
2    6
dtype: int64
```

NumPy ufuncs are safe to apply to `Series` backed by non-ndarray arrays, for example `arrays.SparseArray` (see sparse.calculation). If possible, the ufunc is applied without converting the underlying data to an ndarray.

Console display

A very large `DataFrame` will be truncated to display them in the console. You can also get a summary using `info()`. (The **baseball** dataset is from the **plyr** R package):

```
In [134]: baseball = pd.read_csv("data/baseball.csv")

In [135]: print(baseball)
       id     player  year  stint team  lg   g   ab  ...   cs  bb    so  ibb  hbp   sh   sf  gidp
0   88641  womacto01  2006      2  CHN  NL  19   50  ...  1.0   4   4.0  0.0  0.0  3.0  0.0   0.0
1   88643  schilcu01  2006      1  BOS  AL  31    2  ...  0.0   0   1.0  0.0  0.0  0.0  0.0   0.0
..    ...        ...   ...    ...  ...  ..  ..  ...  ...  ...  ..   ...  ...  ...  ...  ...   ...
98  89533   aloumo01  2007      1  NYN  NL  87  328  ...  0.0  27  30.0  5.0  2.0  0.0  3.0  13.0
99  89534  alomasa02  2007      1  NYN  NL   8   22  ...  0.0   0   3.0  0.0  0.0  0.0  0.0   0.0

[100 rows x 23 columns]

In [136]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 23 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   id      100 non-null    int64  
 1   player  100 non-null    object 
 2   year    100 non-null    int64  
 3   stint   100 non-null    int64  
 4   team    100 non-null    object 
 5   lg      100 non-null    object 
 6   g       100 non-null    int64  
 7   ab      100 non-null    int64  
 8   r       100 non-null    int64  
 9   h       100 non-null    int64  
 10  X2b     100 non-null    int64  
 11  X3b     100 non-null    int64  
 12  hr      100 non-null    int64  
 13  rbi     100 non-null    float64
 14  sb      100 non-null    float64
 15  cs      100 non-null    float64
 16  bb      100 non-null    int64  
 17  so      100 non-null    float64
 18  ibb     100 non-null    float64
 19  hbp     100 non-null    float64
 20  sh      100 non-null    float64
 21  sf      100 non-null    float64
 22  gidp    100 non-null    float64
dtypes: float64(9), int64(11), object(3)
memory usage: 18.1+ KB
```

However, using `DataFrame.to_string()` will return a string representation of the `DataFrame` in tabular form, though it won't always fit the console width:

```
In [137]: print(baseball.iloc[-20:, :12].to_string())
       id     player  year  stint team  lg    g   ab   r    h  X2b  X3b
80  89474  finlest01  2007      1  COL  NL   43   94   9   17    3    0
81  89480  embreal01  2007      1  OAK  AL    4    0   0    0    0    0
82  89481  edmonji01  2007      1  SLN  NL  117  365  39   92   15    2
```