pandas

March 21, 2022

1 PANDAS TUTORIAL (QUICK TOUR-10 MINUTES)

This is a short introduction to `pandas`, geared mainly for new users.

Customarily, we import as follow:

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

1.1 Object Creation

Creating a **Series** by passing a list of values, letting `pandas` create a default integer index.

[ ]:
```
s = pd.Series([1, 2, -7, 10, np.nan, 8, 11])
s
```

[ ]:
```
0     1.0
1     2.0
2    -7.0
3    10.0
4     NaN
5     8.0
6    11.0
dtype: float64
```

Creating a **DataFrame** by passing a `NumPy` array, with datetime index and labeled columns.

[ ]:
```
dates = pd.date_range("20220319", periods=7)
dates
```

[ ]:
```
DatetimeIndex(['2022-03-19', '2022-03-20', '2022-03-21', '2022-03-22',
               '2022-03-23', '2022-03-24', '2022-03-25'],
              dtype='datetime64[ns]', freq='D')
```

[ ]:
```
df = pd.DataFrame(np.random.randn(7, 4), index=dates, columns=list("ABCD"))
df
```

[ ]:
```
                   A         B         C         D
2022-03-19  0.228181  0.411725 -0.888684 -0.907902
2022-03-20 -1.676719  1.090258 -1.966077  0.909066
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163
2022-03-22  1.776478  0.235238 -0.093981  0.867664
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645
2022-03-24 -0.216682  0.182571  0.885816 -0.151794
2022-03-25  0.624784 -0.974044  1.100455  0.893449
```

Create a **DataFrame** by passing a *dictionary* of objects that can be converted into a series-like structure.

[ ]:
```
df2 = pd.DataFrame(
    {
        "A": 1.5,
        "B": pd.Timestamp("20220319"),
        "C": pd.Series(1, index=list(range(4)), dtype=np.float32),
        "D": np.array([5] * 4, dtype=np.int32),
        "E": pd.Categorical(["test", "train", "test", "train"]),
        "F": "foo",
    }
)
df2
```

[ ]:
```
     A          B    C  D      E    F
0  1.5 2022-03-19  1.0  5   test  foo
1  1.5 2022-03-19  1.0  5  train  foo
2  1.5 2022-03-19  1.0  5   test  foo
3  1.5 2022-03-19  1.0  5  train  foo
```

The columns of the resulting **DataFrame** have different `dtypes`.

[ ]:
```
df2.dtypes
```

[ ]:
```
A           float64
B    datetime64[ns]
C           float32
D             int32
E          category
F            object
dtype: object
```

1.2 Viewing data

Here is how to view the top and bottom rows of the frame.

[ ]:
```
df.head()
```

[ ]:
```
                   A         B         C         D
2022-03-19  0.228181  0.411725 -0.888684 -0.907902
2022-03-20 -1.676719  1.090258 -1.966077  0.909066
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163
2022-03-22  1.776478  0.235238 -0.093981  0.867664
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645
```

[ ]:
```
df.tail()
```

[ ]:
```
                   A         B         C         D
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163
2022-03-22  1.776478  0.235238 -0.093981  0.867664
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645
2022-03-24 -0.216682  0.182571  0.885816 -0.151794
2022-03-25  0.624784 -0.974044  1.100455  0.893449
```

You can pass arguments to the `head()` or `tail()` functions to display a specified number of rows.

[ ]:
```
df.head(2)
```

[ ]:
```
                   A         B         C         D
2022-03-19  0.228181  0.411725 -0.888684 -0.907902
2022-03-20 -1.676719  1.090258 -1.966077  0.909066
```

Display the index, columns.

[ ]:
```
df.index
```

[ ]:
```
DatetimeIndex(['2022-03-19', '2022-03-20', '2022-03-21', '2022-03-22',
               '2022-03-23', '2022-03-24', '2022-03-25'],
              dtype='datetime64[ns]', freq='D')
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['A', 'B', 'C', 'D'], dtype='object')
```

`DataFrame.to_numpy()` gives a `NumPy` representation of the underlying data. Note that this can be an expensive operation when your `DataFrame` has columns with *different* data types, which comes down to a fundamental difference between pandas and `NumPy`: `NumPy` arrays have one dtype for the entire array, while pandas DataFrames have one dtype per column. When you call `DataFrame.to_numpy()`, pandas will find the `NumPy` dtype that can hold all of the dtypes in the `DataFrame`. This may end up being object, which requires casting every value to a Python object.

For `df`, our **DataFrame** of all floating-point values, `DataFrame.to_numpy()` is fast and doesn't require copying data

[ ]:
```
df.to_numpy()
```

[ ]:
```
array([[ 0.22818121,  0.41172466, -0.88868392, -0.90790186],
       [-1.67671899,  1.09025807, -1.96607677,  0.90906625],
       [ 0.24424891, -0.2565773 , -0.09908294, -0.16916329],
       [ 1.77647805,  0.23523834, -0.09398143,  0.86766426],
       [-0.18507631, -0.96474687, -0.54284961, -0.28364508],
       [-0.21668238,  0.18257144,  0.88581603, -0.15179394],
       [ 0.62478439, -0.97404414,  1.10045518,  0.893449  ]])
```

For `df2`, the **DataFrame** with multiply `dtypes`, `DataFrame.to_numpy()` is relative expensive.

[ ]:
```
df2.to_numpy()
```

[ ]:
```
array([[1.5, Timestamp('2022-03-19 00:00:00'), 1.0, 5, 'test', 'foo'],
       [1.5, Timestamp('2022-03-19 00:00:00'), 1.0, 5, 'train', 'foo'],
       [1.5, Timestamp('2022-03-19 00:00:00'), 1.0, 5, 'test', 'foo'],
       [1.5, Timestamp('2022-03-19 00:00:00'), 1.0, 5, 'train', 'foo']],
      dtype=object)
```

`describe()` shows a quick statistic summary of your data.

[ ]:
```
df.describe()
```

[ ]:
```
              A         B         C         D
count  7.000000  7.000000  7.000000  7.000000
mean   0.113602 -0.039368 -0.229200  0.165382
std    1.037642  0.750703  1.048530  0.723698
min   -1.676719 -0.974044 -1.966077 -0.907902
25%   -0.200879 -0.610662 -0.715767 -0.226404
50%    0.228181  0.182571 -0.099083 -0.151794
75%    0.434517  0.323481  0.395917  0.880557
max    1.776478  1.090258  1.100455  0.909066
```

[ ]:
```
df2.describe()
```

[ ]:
```
         A    C    D
count  4.0  4.0  4.0
mean   1.5  1.0  5.0
std    0.0  0.0  0.0
min    1.5  1.0  5.0
25%    1.5  1.0  5.0
50%    1.5  1.0  5.0
75%    1.5  1.0  5.0
max    1.5  1.0  5.0
```

Transposing your data.

[ ]:
```
df.T
```

[ ]:
```
   2022-03-19  2022-03-20  2022-03-21  2022-03-22  2022-03-23  2022-03-24  \
A    0.228181   -1.676719    0.244249    1.776478   -0.185076   -0.216682
B    0.411725    1.090258   -0.256577    0.235238   -0.964747    0.182571
C   -0.888684   -1.966077   -0.099083   -0.093981   -0.542850    0.885816
D   -0.907902    0.909066   -0.169163    0.867664   -0.283645   -0.151794

   2022-03-25
A    0.624784
B   -0.974044
C    1.100455
D    0.893449
```

Sorting by an **axis**

[ ]:
```
df.sort_index(axis=0, ascending=False)
```

[ ]:
```
                   A         B         C         D
2022-03-25  0.624784 -0.974044  1.100455  0.893449
2022-03-24 -0.216682  0.182571  0.885816 -0.151794
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645
2022-03-22  1.776478  0.235238 -0.093981  0.867664
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163
2022-03-20 -1.676719  1.090258 -1.966077  0.909066
2022-03-19  0.228181  0.411725 -0.888684 -0.907902
```

[ ]:
```
df.sort_index(axis=1, ascending=False)
```

[ ]:
```
                   D         C         B         A
2022-03-19 -0.907902 -0.888684  0.411725  0.228181
2022-03-20  0.909066 -1.966077  1.090258 -1.676719
2022-03-21 -0.169163 -0.099083 -0.256577  0.244249
2022-03-22  0.867664 -0.093981  0.235238  1.776478
2022-03-23 -0.283645 -0.542850 -0.964747 -0.185076
2022-03-24 -0.151794  0.885816  0.182571 -0.216682
2022-03-25  0.893449  1.100455 -0.974044  0.624784
```

Sorting by values.

[ ]:
```
df.sort_values(by="B")
```

[ ]:
```
                   A         B         C         D
2022-03-25  0.624784 -0.974044  1.100455  0.893449
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163
2022-03-24 -0.216682  0.182571  0.885816 -0.151794
2022-03-22  1.776478  0.235238 -0.093981  0.867664
2022-03-19  0.228181  0.411725 -0.888684 -0.907902
2022-03-20 -1.676719  1.090258 -1.966077  0.909066
```

1.3 Selection

1.3.1 Getting

Selecting a single column, which yeild a `Series`, equivalent to `df.A`.

[ ]:
```
print("df.A", df.A, sep="\n")
print("="*30)
print("df[\"A\"]", df["A"], sep="\n")
```

```
df.A
2022-03-19    0.228181
2022-03-20   -1.676719
2022-03-21    0.244249
2022-03-22    1.776478
2022-03-23   -0.185076
2022-03-24   -0.216682
2022-03-25    0.624784
Freq: D, Name: A, dtype: float64
==============================
df["A"]
2022-03-19    0.228181
2022-03-20   -1.676719
2022-03-21    0.244249
2022-03-22    1.776478
2022-03-23   -0.185076
2022-03-24   -0.216682
2022-03-25    0.624784
Freq: D, Name: A, dtype: float64
```

Selecting via `[]`, which slicing the rows.

[ ]:
```
df[0:3]
```

[ ]:

	A	B	C	D
2022-03-19	0.228181	0.411725	-0.888684	-0.907902
2022-03-20	-1.676719	1.090258	-1.966077	0.909066
2022-03-21	0.244249	-0.256577	-0.099083	-0.169163

[ ]:
```
df["20220319":"20220321"]
```

[ ]:

	A	B	C	D
2022-03-19	0.228181	0.411725	-0.888684	-0.907902
2022-03-20	-1.676719	1.090258	-1.966077	0.909066
2022-03-21	0.244249	-0.256577	-0.099083	-0.169163

1.4 Selection by label

For getting a cross section using a label.

[ ]:
```
df.loc[dates[0]]
```

[ ]:
```
A    0.228181
B    0.411725
C   -0.888684
D   -0.907902
Name: 2022-03-19 00:00:00, dtype: float64
```

Selecting on a multi-axis by label.

[ ]:
```
df.loc[:, ["A", "B"]]
```

[ ]:
```
                   A         B
2022-03-19  0.228181  0.411725
2022-03-20 -1.676719  1.090258
2022-03-21  0.244249 -0.256577
2022-03-22  1.776478  0.235238
2022-03-23 -0.185076 -0.964747
2022-03-24 -0.216682  0.182571
2022-03-25  0.624784 -0.974044
```

Showing label slicing, both endpoints are included.

[ ]:
```
df.loc["20220319":"20220321", ["C", "D"]]
```

[ ]:
```
                   C         D
2022-03-19 -0.888684 -0.907902
2022-03-20 -1.966077  0.909066
2022-03-21 -0.099083 -0.169163
```

Reduction in the dimensions of returned object.

[ ]:
```
df.loc["20220324", ["B", "C"]]
```

[ ]:
```
B    0.182571
C    0.885816
Name: 2022-03-24 00:00:00, dtype: float64
```

For getting a scalar value.

[ ]:
```
df.loc[dates[1], "A"]
```

[ ]:
```
-1.6767189854604438
```

For getting fast access to a scalar (equivalent to the prior method).

```
[ ]: df.at[dates[1], "A"]
```

```
[ ]: -1.6767189854604438
```

1.5 Selection by position

Select via the position of the passed integers.

```
[ ]: df.iloc[3]
     # equivalent to df.loc[dates[3]]
```

```
[ ]: A    1.776478
     B    0.235238
     C   -0.093981
     D    0.867664
     Name: 2022-03-22 00:00:00, dtype: float64
```

By integer slices, acting similar to `Numpy/Python`.

```
[ ]: df.iloc[3:5, 0:2]
     # equivalent to df.loc["20220322":"20220323", ["A", "B"]]
```

```
[ ]:                    A         B
     2022-03-22  1.776478  0.235238
     2022-03-23 -0.185076 -0.964747
```

By list of integer position locations, similar to the `Numpy/Python` style.

```
[ ]: df.iloc[[1, 2, 4], [0, 2]]
     # equivalent to df.loc["20220320":"20220323", ["B", "C"]]
```

```
[ ]:                    A         C
     2022-03-20 -1.676719 -1.966077
     2022-03-21  0.244249 -0.099083
     2022-03-23 -0.185076 -0.542850
```

For slicing rows explicitly.

```
[ ]: df.iloc[1:3, :]
```

```
[ ]:                    A         B         C         D
     2022-03-20 -1.676719  1.090258 -1.966077  0.909066
     2022-03-21  0.244249 -0.256577 -0.099083 -0.169163
```

For slicing columns explicitly.

```
[ ]: df.iloc[:, 1:3]
```

[ ]:

	B	C
2022-03-19	0.411725	-0.888684
2022-03-20	1.090258	-1.966077
2022-03-21	-0.256577	-0.099083
2022-03-22	0.235238	-0.093981
2022-03-23	-0.964747	-0.542850
2022-03-24	0.182571	0.885816
2022-03-25	-0.974044	1.100455

For getting a value explicitly.

[ ]:
```
df.iloc[1, 1]
```

[ ]: 1.0902580667797517

For getting fast access to a scalar (equivalent to the prior method).

[ ]:
```
df.iat[1, 1]
```

[ ]: 1.0902580667797517

1.6 Boolean indexing

Using a single column's values to select data.

[ ]:
```
df[df["A"] > 0]
```

[ ]:

	A	B	C	D
2022-03-19	0.228181	0.411725	-0.888684	-0.907902
2022-03-21	0.244249	-0.256577	-0.099083	-0.169163
2022-03-22	1.776478	0.235238	-0.093981	0.867664
2022-03-25	0.624784	-0.974044	1.100455	0.893449

Selecting values from a **DataFrame** where a boolean condition is met.

[ ]:
```
df[df > 0]
```

[ ]:

	A	B	C	D
2022-03-19	0.228181	0.411725	NaN	NaN
2022-03-20	NaN	1.090258	NaN	0.909066
2022-03-21	0.244249	NaN	NaN	NaN
2022-03-22	1.776478	0.235238	NaN	0.867664
2022-03-23	NaN	NaN	NaN	NaN
2022-03-24	NaN	0.182571	0.885816	NaN
2022-03-25	0.624784	NaN	1.100455	0.893449

Using `isin()` method for filtering.

[ ]:
```
df_copy = df.copy()
df_copy["E"] = ["one", "two", "three", "four", "five", "six", "seven"]
df_copy
```

[ ]:
```
                   A         B         C         D      E
2022-03-19  0.228181  0.411725 -0.888684 -0.907902    one
2022-03-20 -1.676719  1.090258 -1.966077  0.909066    two
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163  three
2022-03-22  1.776478  0.235238 -0.093981  0.867664   four
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645   five
2022-03-24 -0.216682  0.182571  0.885816 -0.151794    six
2022-03-25  0.624784 -0.974044  1.100455  0.893449  seven
```

[ ]:
```
df_copy[df_copy["E"].isin(["three", "six"])]
```

[ ]:
```
                   A         B         C         D      E
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163  three
2022-03-24 -0.216682  0.182571  0.885816 -0.151794    six
```

1.7 Setting

Setting a new column automatically aligns the data by the indexes.

[ ]:
```
s1 = pd.Series(list(range(1, 8)), index=pd.date_range("20220319", periods=7))
s1
```

[ ]:
```
2022-03-19    1
2022-03-20    2
2022-03-21    3
2022-03-22    4
2022-03-23    5
2022-03-24    6
2022-03-25    7
Freq: D, dtype: int64
```

[ ]:
```
df["F"] = s1
df
```

[ ]:
```
                   A         B         C         D  F
2022-03-19  0.228181  0.411725 -0.888684 -0.907902  1
2022-03-20 -1.676719  1.090258 -1.966077  0.909066  2
2022-03-21  0.244249 -0.256577 -0.099083 -0.169163  3
2022-03-22  1.776478  0.235238 -0.093981  0.867664  4
2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645  5
2022-03-24 -0.216682  0.182571  0.885816 -0.151794  6
2022-03-25  0.624784 -0.974044  1.100455  0.893449  7
```

Setting values by label.

```
[ ]: df.at[dates[0], "A"] = 0
     df
```

```
[ ]:                    A         B         C         D  F
     2022-03-19  0.000000  0.411725 -0.888684 -0.907902  1
     2022-03-20 -1.676719  1.090258 -1.966077  0.909066  2
     2022-03-21  0.244249 -0.256577 -0.099083 -0.169163  3
     2022-03-22  1.776478  0.235238 -0.093981  0.867664  4
     2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645  5
     2022-03-24 -0.216682  0.182571  0.885816 -0.151794  6
     2022-03-25  0.624784 -0.974044  1.100455  0.893449  7
```

Setting values by position.

```
[ ]: df.iat[0, 1] = 1
     df
```

```
[ ]:                    A         B         C         D  F
     2022-03-19  0.000000  1.000000 -0.888684 -0.907902  1
     2022-03-20 -1.676719  1.090258 -1.966077  0.909066  2
     2022-03-21  0.244249 -0.256577 -0.099083 -0.169163  3
     2022-03-22  1.776478  0.235238 -0.093981  0.867664  4
     2022-03-23 -0.185076 -0.964747 -0.542850 -0.283645  5
     2022-03-24 -0.216682  0.182571  0.885816 -0.151794  6
     2022-03-25  0.624784 -0.974044  1.100455  0.893449  7
```

Setting by assigning with a `Numpy` array

```
[ ]: df.loc[:, "D"] = np.array(5 * len(df))
     df
```

```
[ ]:                    A         B         C   D  F
     2022-03-19  0.000000  1.000000 -0.888684  35  1
     2022-03-20 -1.676719  1.090258 -1.966077  35  2
     2022-03-21  0.244249 -0.256577 -0.099083  35  3
     2022-03-22  1.776478  0.235238 -0.093981  35  4
     2022-03-23 -0.185076 -0.964747 -0.542850  35  5
     2022-03-24 -0.216682  0.182571  0.885816  35  6
     2022-03-25  0.624784 -0.974044  1.100455  35  7
```

1.8 Missing data

`Pandas` primarily uses the value `np.nan` to represent missing data. It is by default not included in computation.

Reindexing allows you to change/add/delete the index on a sepecified axis. This returns a copy of data.

[ ]:
```
df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ["E"])
df1.loc[dates[0]:dates[1], "E"] = 1
df1
```

[ ]:
```
                   A         B         C   D  F    E
2022-03-19  0.000000  1.000000 -0.888684  35  1  1.0
2022-03-20 -1.676719  1.090258 -1.966077  35  2  1.0
2022-03-21  0.244249 -0.256577 -0.099083  35  3  NaN
2022-03-22  1.776478  0.235238 -0.093981  35  4  NaN
```

To drop any rows that have missing data.

[ ]:
```
df1.dropna(how="any")
```

[ ]:
```
                   A         B         C   D  F    E
2022-03-19  0.000000  1.000000 -0.888684  35  1  1.0
2022-03-20 -1.676719  1.090258 -1.966077  35  2  1.0
```

Filling missing data.

[ ]:
```
df1.fillna(value=3)
```

[ ]:
```
                   A         B         C   D  F    E
2022-03-19  0.000000  1.000000 -0.888684  35  1  1.0
2022-03-20 -1.676719  1.090258 -1.966077  35  2  1.0
2022-03-21  0.244249 -0.256577 -0.099083  35  3  3.0
2022-03-22  1.776478  0.235238 -0.093981  35  4  3.0
```

To get the boolean mask where values are `nan`.

[ ]:
```
pd.isna(df1)
```

[ ]:
```
                A      B      C      D      F      E
2022-03-19  False  False  False  False  False  False
2022-03-20  False  False  False  False  False  False
2022-03-21  False  False  False  False  False   True
2022-03-22  False  False  False  False  False   True
```

1.9 Operations

1.9.1 Stats

Operations in general *exclude* missing data.

Perform a descriptive statistic.

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

[ ]:
```
A     0.081005
B     0.044671
C    -0.229200
D    35.000000
F     4.000000
dtype: float64
```

Same operation on the other axis.

[ ]:
```
df.mean(1)
```

[ ]:
```
2022-03-19    7.222263
2022-03-20    6.889492
2022-03-21    7.577718
2022-03-22    8.183547
2022-03-23    7.661465
2022-03-24    8.370341
2022-03-25    8.550239
Freq: D, dtype: float64
```

Operation with objects that have different dismensionality and need alignment. In addition, `pandas` automatically broadcast along the specified dimension.

[ ]:
```
s = pd.Series([1, 3, 5, np.nan, 6, 8, 11], index=dates).shift(2)
s
```

[ ]:
```
2022-03-19    NaN
2022-03-20    NaN
2022-03-21    1.0
2022-03-22    3.0
2022-03-23    5.0
2022-03-24    NaN
2022-03-25    6.0
Freq: D, dtype: float64
```

[ ]:
```
df.sub(s, axis="index")
```

[ ]:

	A	B	C	D	F
2022-03-19	NaN	NaN	NaN	NaN	NaN
2022-03-20	NaN	NaN	NaN	NaN	NaN
2022-03-21	-0.755751	-1.256577	-1.099083	34.0	2.0
2022-03-22	-1.223522	-2.764762	-3.093981	32.0	1.0
2022-03-23	-5.185076	-5.964747	-5.542850	30.0	0.0
2022-03-24	NaN	NaN	NaN	NaN	NaN
2022-03-25	-5.375216	-6.974044	-4.899545	29.0	1.0

1.9.2 Apply

Applying functions to the data.

[ ]:
```
df
```

[ ]:
```
                   A         B         C   D  F
2022-03-19  0.000000  1.000000 -0.888684  35  1
2022-03-20 -1.676719  1.090258 -1.966077  35  2
2022-03-21  0.244249 -0.256577 -0.099083  35  3
2022-03-22  1.776478  0.235238 -0.093981  35  4
2022-03-23 -0.185076 -0.964747 -0.542850  35  5
2022-03-24 -0.216682  0.182571  0.885816  35  6
2022-03-25  0.624784 -0.974044  1.100455  35  7
```

[ ]:
```
df.apply(np.cumsum)
# equivalent to df.apply(np.cumsum, axis=0)
```

[ ]:
```
                   A         B         C    D   F
2022-03-19  0.000000  1.000000 -0.888684   35   1
2022-03-20 -1.676719  2.090258 -2.854761   70   3
2022-03-21 -1.432470  1.833681 -2.953844  105   6
2022-03-22  0.344008  2.068919 -3.047825  140  10
2022-03-23  0.158932  1.104172 -3.590675  175  15
2022-03-24 -0.057751  1.286744 -2.704859  210  21
2022-03-25  0.567034  0.312700 -1.604403  245  28
```

[ ]:
```
df.apply(np.cumsum, axis=1)
```

[ ]:
```
                   A         B         C          D          F
2022-03-19  0.000000  1.000000  0.111316  35.111316  36.111316
2022-03-20 -1.676719 -0.586461 -2.552538  32.447462  34.447462
2022-03-21  0.244249 -0.012328 -0.111411  34.888589  37.888589
2022-03-22  1.776478  2.011716  1.917735  36.917735  40.917735
2022-03-23 -0.185076 -1.149823 -1.692673  33.307327  38.307327
2022-03-24 -0.216682 -0.034111  0.851705  35.851705  41.851705
2022-03-25  0.624784 -0.349260  0.751195  35.751195  42.751195
```

[ ]:
```
df.apply(lambda x: x.max() - x.min())
```

[ ]:
```
A    3.453197
B    2.064302
C    3.066532
D    0.000000
F    6.000000
dtype: float64
```

[ ]:
```
df.apply(lambda x: x.max() - x.min(), axis=1)
```

```
[ ]: 2022-03-19    35.888684
     2022-03-20    36.966077
     2022-03-21    35.256577
     2022-03-22    35.093981
     2022-03-23    35.964747
     2022-03-24    35.216682
     2022-03-25    35.974044
     Freq: D, dtype: float64
```

1.9.3 Histogramming

```
[ ]: s = pd.Series(np.random.randint(0, 7, size=10))
     s
```

```
[ ]: 0    6
     1    0
     2    4
     3    4
     4    1
     5    2
     6    0
     7    6
     8    1
     9    2
     dtype: int32
```

```
[ ]: s.value_counts()
```

```
[ ]: 6    2
     0    2
     4    2
     1    2
     2    2
     dtype: int64
```

1.9.4 String methods

Series is equipped with a set of string processing methods in the `str` attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in `str` generally uses **regular expressions** by default (and in some cases always uses them).

```
[ ]: s = pd.Series(["A", "B", "C", "D", "Aaba", "Baca", np.nan, "CABA", "dog",␣
      ↪"cat"])
     s
```

[ ]:
```
0       A
1       B
2       C
3       D
4    Aaba
5    Baca
6     NaN
7    CABA
8     dog
9     cat
dtype: object
```

[ ]:
```
s.str.lower()
```

[ ]:
```
0       a
1       b
2       c
3       d
4    aaba
5    baca
6     NaN
7    caba
8     dog
9     cat
dtype: object
```

1.9.5 Merge

Concat `Pandas` provides various facilities for easily combining together `Series` and `DataFrame` objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join/merge-type operations.

Concatenating pandas objects together with `concat()`.

[ ]:
```
df = pd.DataFrame(np.random.randn(10, 4))
df
```

[ ]:
```
          0         1         2         3
0 -1.724109  0.411101 -0.328557  0.250358
1 -1.254807  1.463416  1.133394 -1.834136
2 -0.607070 -1.460862 -0.433120 -0.098387
3 -0.236818  0.420965 -0.356506  0.323899
4 -0.603135  1.060861  0.405774 -0.511619
5 -0.582767 -0.639265 -0.033607 -0.469928
6 -0.339338  0.181223  0.228185  0.822008
7  0.213306 -0.992878  0.517584  0.304642
8 -1.147936 -0.083162 -0.256240  0.034513
```

```
9  0.266978 -0.413701  0.114007  0.177897
```

[ ]:
```
# break it into pieces
pieces = [df[:3], df[3:7], df[7:]]
pieces
```

[ ]:
```
[          0         1         2         3
 0 -1.724109  0.411101 -0.328557  0.250358
 1 -1.254807  1.463416  1.133394 -1.834136
 2 -0.607070 -1.460862 -0.433120 -0.098387,
           0         1         2         3
 3 -0.236818  0.420965 -0.356506  0.323899
 4 -0.603135  1.060861  0.405774 -0.511619
 5 -0.582767 -0.639265 -0.033607 -0.469928
 6 -0.339338  0.181223  0.228185  0.822008,
           0         1         2         3
 7  0.213306 -0.992878  0.517584  0.304642
 8 -1.147936 -0.083162 -0.256240  0.034513
 9  0.266978 -0.413701  0.114007  0.177897]
```

[ ]:
```
pd.concat(pieces)
```

[ ]:
```
          0         1         2         3
0 -1.724109  0.411101 -0.328557  0.250358
1 -1.254807  1.463416  1.133394 -1.834136
2 -0.607070 -1.460862 -0.433120 -0.098387
3 -0.236818  0.420965 -0.356506  0.323899
4 -0.603135  1.060861  0.405774 -0.511619
5 -0.582767 -0.639265 -0.033607 -0.469928
6 -0.339338  0.181223  0.228185  0.822008
7  0.213306 -0.992878  0.517584  0.304642
8 -1.147936 -0.083162 -0.256240  0.034513
9  0.266978 -0.413701  0.114007  0.177897
```

Adding a column to a `DataFrame` is relatively fast. However, adding a row requires a copy, and may be expensive. I recommend passing a pre-built list of records to the `DataFrame` constructor instead of building a `DataFrame` by iteratively appending records to it.

1.9.6 Join

SQL style merges.

[ ]:
```
left = pd.DataFrame(
    {
        "keys": ["foo", "bar"],
        "lval": [1, 2]
```

```
    }
)
right = pd.DataFrame(
    {
        "keys": ["foo", "bar"],
        "rval": [4, 5]
    }
)
```

[ ]:
```
left
```

[ ]:

	keys	lval
0	foo	1
1	bar	2

[ ]:
```
right
```

[ ]:

	keys	rval
0	foo	4
1	bar	5

[ ]:
```
pd.merge(left, right, on="keys")
```

[ ]:

	keys	lval	rval
0	foo	1	4
1	bar	2	5

1.10 Grouping

By ”grouping” we are refering to a process involving one ore more of the following steps:

- **Splitting** the data into groups based on some criteria.
- **Applying** a function to each group independently
- **Combining** the results into a data structure

[ ]:
```
df = pd.DataFrame(
    {
        "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
        "B": ["one", "one", "two", "three", "two", "two", "one", "three"],
        "C": np.random.randn(8),
        "D": np.random.randn(8),
    }
)
df
```

[ ]:

	A	B	C	D
0	foo	one	0.338328	0.407254

```
1  bar    one  1.277655  0.088752
2  foo    two -0.725769  1.240329
3  bar  three -0.326743 -0.559055
4  foo    two -0.089508 -0.495114
5  bar    two -0.082540 -0.471225
6  foo    one -1.126816 -0.151158
7  foo  three  2.010950  1.234230
```

Grouping and then applying the `sum()` function to the resulting group.

[ ]:
```
df.groupby("A").sum()
```

[ ]:
```
            C         D
A
bar  0.868371 -0.941528
foo  0.407185  2.235541
```

Grouping by multiple columns forms a hierarchical index, and again we can apply the `sum()` function.

[ ]:
```
df.groupby(["A", "B"]).sum()
```

[ ]:
```
                  C         D
A   B
bar one    1.277655  0.088752
    three -0.326743 -0.559055
    two   -0.082540 -0.471225
foo one   -0.788489  0.256096
    three  2.010950  1.234230
    two   -0.815277  0.745215
```

1.11 Reshaping

1.11.1 Stack

[ ]:
```
tuples = list(
    zip(
        *[
            ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
            ["one", "two", "one", "two", "one", "two", "one", "two"],
        ]
    )
)
index = pd.MultiIndex.from_tuples(tuples, names=["first", "second"])
df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=["A", "B"])
df
```

```
[ ]:                        A         B
     first second
     bar   one     0.530897 -0.825297
           two    -0.296452 -0.448199
     baz   one     0.953647 -0.304044
           two    -0.871343 -1.245235
     foo   one    -0.405061 -0.422861
           two    -0.973405 -0.167809
     qux   one     0.399787 -0.243971
           two     2.014824 -1.222681
```

The `stack()` method "compress" a level in the **DataFrame's** columns.

```
[ ]: df2 = df[:4]
     df2
```

```
[ ]:                        A         B
     first second
     bar   one     0.530897 -0.825297
           two    -0.296452 -0.448199
     baz   one     0.953647 -0.304044
           two    -0.871343 -1.245235
```

```
[ ]: stacked = df2.stack()
     stacked
```

```
[ ]: first  second
     bar    one     A    0.530897
                    B   -0.825297
            two     A   -0.296452
                    B   -0.448199
     baz    one     A    0.953647
                    B   -0.304044
            two     A   -0.871343
                    B   -1.245235
     dtype: float64
```

With a "stacked" DataFrame or Series (having a `MultiIndex` as the `Index`), the inverse operation of `stack()` is `unstack()`, which by default unstacks the **last level**.

```
[ ]: stacked.unstack()
```

```
[ ]:                        A         B
     first second
     bar   one     0.530897 -0.825297
           two    -0.296452 -0.448199
     baz   one     0.953647 -0.304044
           two    -0.871343 -1.245235
```

[ ]:
```
stacked.unstack(1)
```

[ ]:
```
second        one       two
first
bar    A  0.530897 -0.296452
       B -0.825297 -0.448199
baz    A  0.953647 -0.871343
       B -0.304044 -1.245235
```

[ ]:
```
stacked.unstack(0)
```

[ ]:
```
first          bar       baz
second
one     A  0.530897  0.953647
        B -0.825297 -0.304044
two     A -0.296452 -0.871343
        B -0.448199 -1.245235
```

1.12 Pivot tables

[ ]:
```
df = pd.DataFrame(
    {
        "A": ["one", "one", "two", "three"] * 3,
        "B": ["A", "B", "C"] * 4,
        "C": ["foo", "foo", "foo", "bar", "bar", "bar"] * 2,
        "D": np.random.randn(12),
        "E": np.random.randn(12),
    }
)

df
```

[ ]:
```
        A  B    C         D         E
0     one  A  foo  1.488596 -0.117750
1     one  B  foo  0.363735 -0.567175
2     two  C  foo -1.184895 -0.880365
3   three  A  bar  1.710122 -0.495467
4     one  B  bar  1.319943 -0.564924
5     one  C  bar  0.061341 -0.416826
6     two  A  foo -0.890777  1.249897
7   three  B  foo -0.062211 -1.280127
8     one  C  foo -0.786301  1.806379
9     one  A  bar  0.341206 -1.359112
10    two  B  bar  1.131091  0.694300
11  three  C  bar -0.550187 -0.010789
```

We can produce pivot tables from this data very easily.

[ ]:
```
pd.pivot_table(df, values="D", index=["A", "B"], columns="C")
```

[ ]:
```
C               bar       foo
A     B
one   A  0.341206  1.488596
      B  1.319943  0.363735
      C  0.061341 -0.786301
three A  1.710122       NaN
      B       NaN -0.062211
      C -0.550187       NaN
two   A       NaN -0.890777
      B  1.131091       NaN
      C       NaN -1.184895
```

1.13 Time series

`Pandas` has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications.

[ ]:
```
rng = pd.date_range("1/1/2022", periods=100, freq="S")
ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
ts
```

[ ]:
```
2022-01-01 00:00:00    251
2022-01-01 00:00:01    489
2022-01-01 00:00:02    348
2022-01-01 00:00:03    206
2022-01-01 00:00:04     42
                      …
2022-01-01 00:01:35    408
2022-01-01 00:01:36    126
2022-01-01 00:01:37    483
2022-01-01 00:01:38     24
2022-01-01 00:01:39    144
Freq: S, Length: 100, dtype: int32
```

[ ]:
```
ts.resample("5Min").sum()
```

[ ]:
```
2022-01-01    25972
Freq: 5T, dtype: int32
```

Time zone representation

[ ]:
```
rng = pd.date_range("1/1/2022 00:00", periods=5, freq="D")
ts = pd.Series(np.random.randn(len(rng)), rng)
ts
```

[ ]:
```
2022-01-01   -0.727610
2022-01-02    0.653522
2022-01-03   -0.104993
2022-01-04   -0.798697
2022-01-05    1.556841
Freq: D, dtype: float64
```

[ ]:
```
ts_utc = ts.tz_localize("UTC")
ts_utc
```

[ ]:
```
2022-01-01 00:00:00+00:00   -0.727610
2022-01-02 00:00:00+00:00    0.653522
2022-01-03 00:00:00+00:00   -0.104993
2022-01-04 00:00:00+00:00   -0.798697
2022-01-05 00:00:00+00:00    1.556841
Freq: D, dtype: float64
```

Converting to another time zone.

[ ]:
```
ts_utc.tz_convert("US/Eastern")
```

[ ]:
```
2021-12-31 19:00:00-05:00   -0.727610
2022-01-01 19:00:00-05:00    0.653522
2022-01-02 19:00:00-05:00   -0.104993
2022-01-03 19:00:00-05:00   -0.798697
2022-01-04 19:00:00-05:00    1.556841
Freq: D, dtype: float64
```

Converting between time span representations.

[ ]:
```
rng = pd.date_range("1/1/2022", periods=5, freq="M")
ts = pd.Series(np.random.randn(len(rng)), index=rng)
ts
```

[ ]:
```
2022-01-31   -0.524220
2022-02-28   -0.768486
2022-03-31   -1.456069
2022-04-30   -1.391087
2022-05-31   -0.413119
Freq: M, dtype: float64
```

[ ]:
```
ps = ts.to_period()
ps
```

[ ]:
```
2022-01   -0.524220
2022-02   -0.768486
2022-03   -1.456069
2022-04   -1.391087
2022-05   -0.413119
Freq: M, dtype: float64
```

[ ]:
```
ps.to_timestamp()
```

[ ]:
```
2022-01-01   -0.524220
2022-02-01   -0.768486
2022-03-01   -1.456069
2022-04-01   -1.391087
2022-05-01   -0.413119
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenients arithmetic functions to be used. In the following example, I convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end.

[ ]:
```
prng = pd.period_range("1990Q1", "2000Q4", freq="Q-NOV")
ts = pd.Series(np.random.randn(len(prng)), prng)
ts.index = (prng.asfreq("M", "e") + 1).asfreq("H", "s") + 9
ts.head()
```

[ ]:
```
1990-03-01 09:00    0.915812
1990-06-01 09:00    0.924666
1990-09-01 09:00    0.366394
1990-12-01 09:00    0.370943
1991-03-01 09:00    0.172963
Freq: H, dtype: float64
```

1.14 Categoricals

Pandas can include categorical data in a **DataFrame**.

[ ]:
```
df = pd.DataFrame(
    {
        "id": list(range(1, 7, 1)),
        "raw_grade": ["a", "a", "b", "a", "a", "e"],
    }
)
```

Converting the grades to a categorical data type.

[ ]:
```
df["grade"] = df["raw_grade"].astype("category")
df["grade"]
```

```
[ ]: 0    a
     1    a
     2    b
     3    a
     4    a
     5    e
     Name: grade, dtype: category
     Categories (3, object): ['a', 'b', 'e']
```

Rename the categories to more meaningful names (assigning to `Series.cat.categories()` is in place!).

```
[ ]: df["grade"].cat.categories = ["very good", "good", "very bad"]
     df["grade"]
```

```
[ ]: 0    very good
     1    very good
     2         good
     3    very good
     4    very good
     5     very bad
     Name: grade, dtype: category
     Categories (3, object): ['very good', 'good', 'very bad']
```

Reorder the categories and simultaneously add the missing categories (methods under `Series.cat()` return a new `Series` by default).

```
[ ]: df["grade"] = df["grade"].cat.set_categories(
         ["very bad", "bad", "medium", "good", "very good"]
     )
     df["grade"]
```

```
[ ]: 0    very good
     1    very good
     2         good
     3    very good
     4    very good
     5     very bad
     Name: grade, dtype: category
     Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']
```

Sorting in per order in the categories, not lexical order.

```
[ ]: df.sort_values(by="grade", ascending=False)
```

```
[ ]:    id raw_grade      grade
     0   1         a  very good
     1   2         a  very good
```

```
3   4          a   very good
4   5          a   very good
2   3          b        good
5   6          e    very bad
```

Grouping by a categorical column also shows empty categories.

[ ]:
```
df.groupby("grade").size()
```

[ ]:
```
grade
very bad     1
bad          0
medium       0
good         1
very good    4
dtype: int64
```

1.15 Plotting

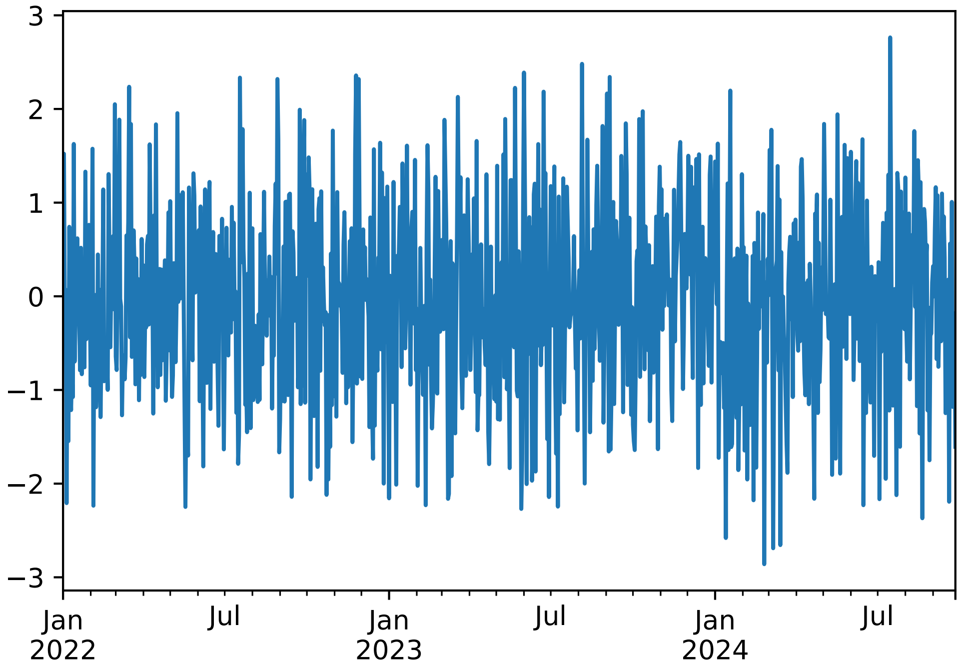
We use the standard convention for referencing the matplotlib API.

[ ]:
```
import matplotlib.pyplot as plt
plt.close("all")
```

The `close()` method is used to close a figure window.

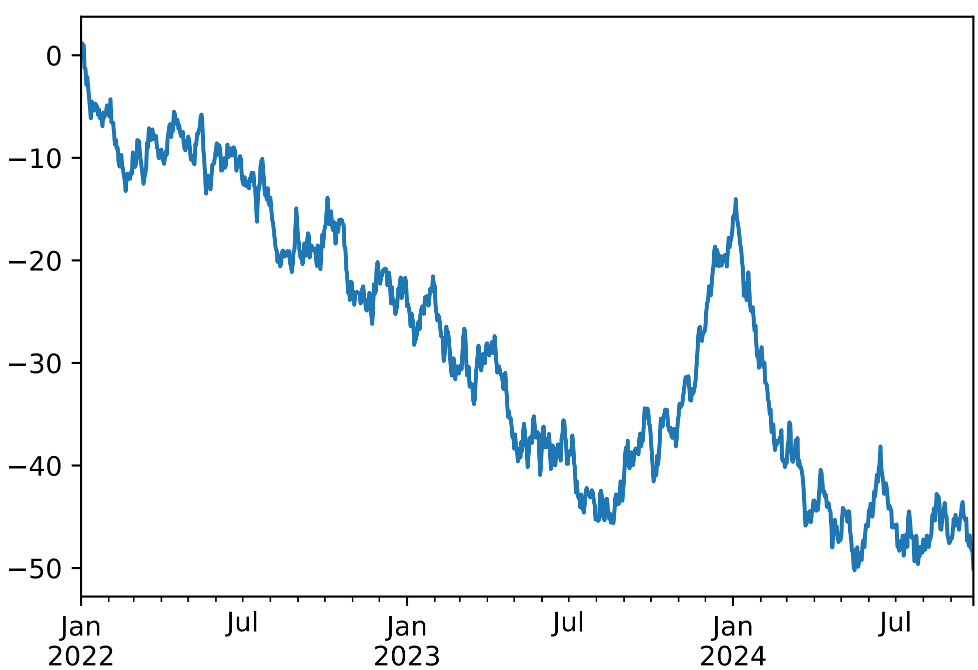
[ ]:
```
ts = pd.Series(np.random.randn(1000), index=pd.date_range("1/1/2022",␣
 ↪periods=1000))
ts.plot()
```

[ ]:
```
<AxesSubplot:>
```



[ ]:
```
ts_cumsum = ts.cumsum()
ts_cumsum.plot()
```

[ ]: <AxesSubplot:>



If running under Jupyter Notebook, the plot will appear on `plot()`. Otherwise use `matplotlib.pyplot.show` to show it of `matplotlin.pyplot.savefig` to write it into a file.

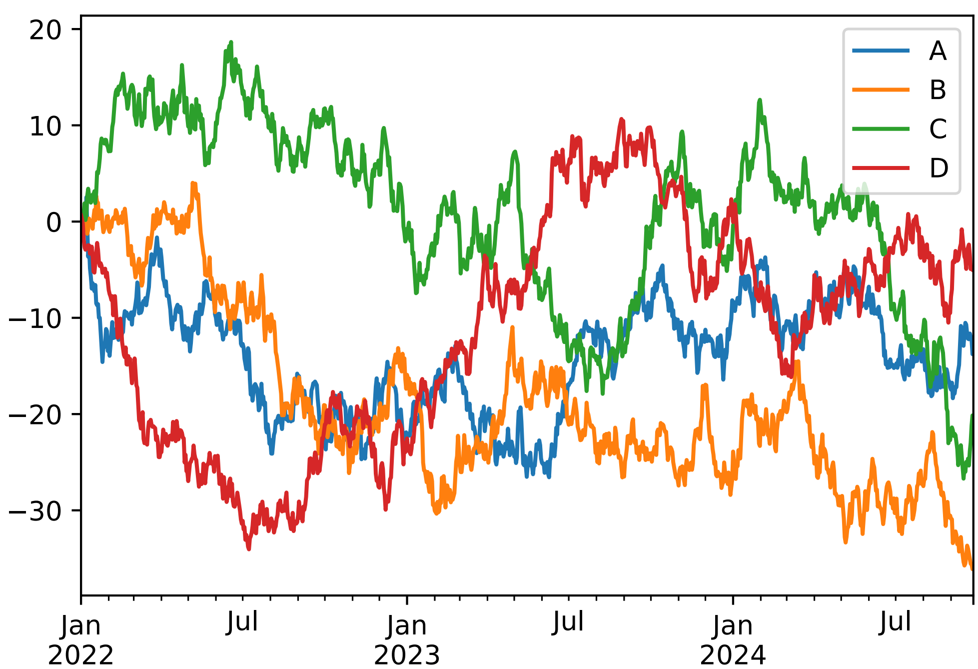
[ ]:
```
plt.show()
```

On a DataFrame, the `plot()` method is a convenience to plot all of the columns with labels.

[ ]:
```
df = pd.DataFrame(
    np.random.randn(1000, 4),
    index=ts.index,
    columns=list("ABCD")
)
df = df.cumsum()
plt.figure()
df.plot()
plt.legend(loc="best")
```

[ ]:
```
<matplotlib.legend.Legend at 0x1e0fd34ec10>
```

```
<Figure size 432x288 with 0 Axes>
```



1.16 Getting data in/out

1.16.1 CSV

Writing to a .csv file

[ ]:
```
df.to_csv("files/foo.csv")
```

Reading from a .csv file

[ ]:
```
pd.read_csv("files/foo.csv")
```

[ ]:
```
     Unnamed: 0          A          B          C          D
0    2022-01-01   0.091463   1.673725  -0.746928   0.857382
1    2022-01-02   0.767879   2.172299  -1.809359   0.242449
2    2022-01-03  -0.188135   3.627265  -0.954293   0.558939
3    2022-01-04  -0.568480   3.282168  -2.156548  -0.169787
4    2022-01-05  -0.031601   1.061619  -3.950347   0.062531
..          …          …          …          …          …
995  2024-09-22 -15.264482 -29.471355 -21.530166  24.533283
996  2024-09-23 -14.416862 -29.069515 -22.524112  23.382795
997  2024-09-24 -14.521215 -28.743473 -21.557216  21.931433
998  2024-09-25 -15.213408 -28.746767 -19.732183  23.176940
999  2024-09-26 -16.628631 -28.289745 -20.632969  24.248229

[1000 rows x 5 columns]
```

1.16.2 HDF5

Reading and writing to HDF5Stores.

Writing to a HDF5 Store.

[ ]:
```
# !pip install tables
df.to_hdf("files/foo.h5", "df")
```

Reading from HDF5 Store.

[ ]:
```
pd.read_hdf("files/foo.h5", "df")
```

[ ]:
```
                    A          B          C          D
2022-01-01   0.091463   1.673725  -0.746928   0.857382
2022-01-02   0.767879   2.172299  -1.809359   0.242449
2022-01-03  -0.188135   3.627265  -0.954293   0.558939
2022-01-04  -0.568480   3.282168  -2.156548  -0.169787
2022-01-05  -0.031601   1.061619  -3.950347   0.062531
…                   …          …          …          …
```

```
2024-09-22 -15.264482 -29.471355 -21.530166  24.533283
2024-09-23 -14.416862 -29.069515 -22.524112  23.382795
2024-09-24 -14.521215 -28.743473 -21.557216  21.931433
2024-09-25 -15.213408 -28.746767 -19.732183  23.176940
2024-09-26 -16.628631 -28.289745 -20.632969  24.248229

[1000 rows x 4 columns]
```

1.16.3 Excel

Reading and writing to MS Excel.

Writing to an excel file

[ ]:
```
df.to_excel("files/foo.xlsx", sheet_name="Sheet1")
```

Reading from an excel file.

[ ]:
```
pd.read_excel("files/foo.xlsx", "Sheet1", index_col=None, na_values=["NA"])
```

[ ]:
```
    Unnamed: 0          A          B          C          D
0   2022-01-01   0.091463   1.673725  -0.746928   0.857382
1   2022-01-02   0.767879   2.172299  -1.809359   0.242449
2   2022-01-03  -0.188135   3.627265  -0.954293   0.558939
3   2022-01-04  -0.568480   3.282168  -2.156548  -0.169787
4   2022-01-05  -0.031601   1.061619  -3.950347   0.062531
..         …          …          …          …          …
995 2024-09-22 -15.264482 -29.471355 -21.530166  24.533283
996 2024-09-23 -14.416862 -29.069515 -22.524112  23.382795
997 2024-09-24 -14.521215 -28.743473 -21.557216  21.931433
998 2024-09-25 -15.213408 -28.746767 -19.732183  23.176940
999 2024-09-26 -16.628631 -28.289745 -20.632969  24.248229

[1000 rows x 5 columns]
```