HW 0 - Intro to Pandas

February 22, 2021

1 HW 0 - Intro to Pandas

Credit: https://pandas.pydata.org/pandas-docs/stable/getting_started/10min.html

[1]:
```
import numpy as np
import pandas as pd
import matplotlib as plt
```

1.1 Object Creation

Creating a Series by passing a list of values, letting pandas create a default integer index:

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

[2]:
```
0    1.0
1    3.0
2    5.0
3    NaN
4    6.0
5    8.0
dtype: float64
```

Creating a DataFrame by passing a NumPy array, with a datetime index and labeled columns:

[3]:
```
dates = pd.date_range('20130101', periods=6)
dates
```

[3]:
```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')
```

[4]:
```
df = pd.DataFrame(np.random.randn(6, 4), index=dates, columns=list('ABCD'))
df
```

[4]:
```
                   A         B         C         D
2013-01-01  0.603855 -1.909945 -0.479259  1.702171
```

```
2013-01-02 -0.641384  0.495139 -2.020046  0.001336
2013-01-03  2.294530 -0.635708 -0.733891 -0.496177
2013-01-04 -0.640988 -0.463833  0.509944  0.435204
2013-01-05 -2.107043 -0.302788  0.607642 -0.051413
2013-01-06  0.738407 -0.186075 -1.822979  0.718949
```

Creating a DataFrame by passing a dict of objects that can be converted to series-like.

[5]:
```
df2 = pd.DataFrame({'A': 1.,
                    'B': pd.Timestamp('20130102'),
                    'C': pd.Series(1, index=list(range(4)), dtype='float32'),
                    'D': np.array([3] * 4, dtype='int32'),
                    'E': pd.Categorical(["test", "train", "test", "train"]),
                    'F': 'foo'})
df2
```

[5]:
```
     A          B    C  D      E    F
0  1.0 2013-01-02  1.0  3   test  foo
1  1.0 2013-01-02  1.0  3  train  foo
2  1.0 2013-01-02  1.0  3   test  foo
3  1.0 2013-01-02  1.0  3  train  foo
```

The columns of the resulting DataFrame have different dtypes.

[6]:
```
df2.dtypes
```

[6]:
```
A           float64
B    datetime64[ns]
C           float32
D             int32
E          category
F            object
dtype: object
```

1.2 Viewing Data

View the top and bottom rows of the frame:

[7]:
```
df.head()
```

[7]:
```
                   A         B         C         D
2013-01-01  0.603855 -1.909945 -0.479259  1.702171
2013-01-02 -0.641384  0.495139 -2.020046  0.001336
2013-01-03  2.294530 -0.635708 -0.733891 -0.496177
2013-01-04 -0.640988 -0.463833  0.509944  0.435204
2013-01-05 -2.107043 -0.302788  0.607642 -0.051413
```

[8]:
```
df.tail(3)
```

[8]:
```
                   A         B         C         D
2013-01-04 -0.640988 -0.463833  0.509944  0.435204
2013-01-05 -2.107043 -0.302788  0.607642 -0.051413
2013-01-06  0.738407 -0.186075 -1.822979  0.718949
```

Display the index, columns:

[9]:
```
df.index
```

[9]:
```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')
```

[10]:
```
df.columns
```

[10]:
```
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.

[11]:
```
df.values
```

[11]:
```
array([[ 6.03855125e-01, -1.90994532e+00, -4.79258947e-01,
         1.70217068e+00],
       [-6.41384404e-01,  4.95138800e-01, -2.02004630e+00,
         1.33590618e-03],
       [ 2.29453036e+00, -6.35708166e-01, -7.33890891e-01,
        -4.96176537e-01],
       [-6.40988010e-01, -4.63832592e-01,  5.09944441e-01,
         4.35203799e-01],
       [-2.10704332e+00, -3.02787590e-01,  6.07641843e-01,
        -5.14128288e-02],
       [ 7.38406723e-01, -1.86074719e-01, -1.82297924e+00,
         7.18948901e-01]])
```

[12]:
```
df2.values
```

[12]:
```
array([[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo'],
```

```
 [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
 [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo']],
dtype=object)
```

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

[13]:
```
df.describe()
```

[13]:
```
              A         B         C         D
count  6.000000  6.000000  6.000000  6.000000
mean   0.041229 -0.500535 -0.656432  0.385012
std    1.511716  0.791885  1.114987  0.769819
min   -2.107043 -1.909945 -2.020046 -0.496177
25%   -0.641285 -0.592739 -1.550707 -0.038226
50%   -0.018566 -0.383310 -0.606575  0.218270
75%    0.704769 -0.215253  0.262644  0.648013
max    2.294530  0.495139  0.607642  1.702171
```

Transposing your data:

[14]:
```
df.T
```

[14]:
```
   2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  2013-01-06
A    0.603855   -0.641384    2.294530   -0.640988   -2.107043    0.738407
B   -1.909945    0.495139   -0.635708   -0.463833   -0.302788   -0.186075
C   -0.479259   -2.020046   -0.733891    0.509944    0.607642   -1.822979
D    1.702171    0.001336   -0.496177    0.435204   -0.051413    0.718949
```

Sorting by an axis:

[17]:
```
df.sort_index(axis=1, ascending=False)
```

[17]:
```
                   D         C         B         A
2013-01-01  1.702171 -0.479259 -1.909945  0.603855
2013-01-02  0.001336 -2.020046  0.495139 -0.641384
2013-01-03 -0.496177 -0.733891 -0.635708  2.294530
2013-01-04  0.435204  0.509944 -0.463833 -0.640988
2013-01-05 -0.051413  0.607642 -0.302788 -2.107043
2013-01-06  0.718949 -1.822979 -0.186075  0.738407
```

Sorting by values:

[18]:
```
df.sort_values(by='B')
```

[18]:
```
                   A         B         C         D
2013-01-01  0.603855 -1.909945 -0.479259  1.702171
2013-01-03  2.294530 -0.635708 -0.733891 -0.496177
2013-01-04 -0.640988 -0.463833  0.509944  0.435204
```

```
2013-01-05 -2.107043 -0.302788  0.607642 -0.051413
2013-01-06  0.738407 -0.186075 -1.822979  0.718949
2013-01-02 -0.641384  0.495139 -2.020046  0.001336
```

1.3 Selection

1.3.1 Getting

Selecting a single column, which yields a Series, equivalent to df.A:

[19]:
```
df['A']
```

[19]:
```
2013-01-01    0.603855
2013-01-02   -0.641384
2013-01-03    2.294530
2013-01-04   -0.640988
2013-01-05   -2.107043
2013-01-06    0.738407
Freq: D, Name: A, dtype: float64
```

Selecting via [ ], which slices the rows.

[20]:
```
df[0:3]
```

[20]:
```
                   A         B         C         D
2013-01-01  0.603855 -1.909945 -0.479259  1.702171
2013-01-02 -0.641384  0.495139 -2.020046  0.001336
2013-01-03  2.294530 -0.635708 -0.733891 -0.496177
```

[21]:
```
df['20130102':'20130104']
```

[21]:
```
                   A         B         C         D
2013-01-02 -0.641384  0.495139 -2.020046  0.001336
2013-01-03  2.294530 -0.635708 -0.733891 -0.496177
2013-01-04 -0.640988 -0.463833  0.509944  0.435204
```

1.3.2 Selection by label

For getting a cross section using a label:

[22]:
```
df.loc[dates[0]]
```

[22]:
```
A    0.603855
B   -1.909945
C   -0.479259
D    1.702171
```

```
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label:

[23]:
```
df.loc[:, ['A', 'B']]
```

[23]:
```
                   A         B
2013-01-01  0.603855 -1.909945
2013-01-02 -0.641384  0.495139
2013-01-03  2.294530 -0.635708
2013-01-04 -0.640988 -0.463833
2013-01-05 -2.107043 -0.302788
2013-01-06  0.738407 -0.186075
```

Showing label slicing, both endpoints are included:

[24]:
```
df.loc['20130102':'20130104', ['A', 'B']]
```

[24]:
```
                   A         B
2013-01-02 -0.641384  0.495139
2013-01-03  2.294530 -0.635708
2013-01-04 -0.640988 -0.463833
```

Reduction in the dimensions of the returned object:

[25]:
```
df.loc['20130102', ['A', 'B']]
```

[25]:
```
A   -0.641384
B    0.495139
Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value:

[26]:
```
df.loc[dates[0], 'A']
```

[26]:
```
0.6038551249768886
```

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

[27]:
```
df.at[dates[0], 'A']
```

[27]:
```
0.6038551249768886
```

1.3.3 Selection by position

Select via the position of the passed integers:

[28]:
```
df.iloc[3]
```

[28]:
```
A   -0.640988
B   -0.463833
C    0.509944
D    0.435204
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python:

[29]:
```
df.iloc[3:5, 0:2]
```

[29]:
```
                   A         B
2013-01-04 -0.640988 -0.463833
2013-01-05 -2.107043 -0.302788
```

By lists of integer position locations, similar to the numpy/python style:

[30]:
```
df.iloc[[1, 2, 4], [0, 2]]
```

[30]:
```
                   A         C
2013-01-02 -0.641384 -2.020046
2013-01-03  2.294530 -0.733891
2013-01-05 -2.107043  0.607642
```

For slicing rows explicitly:

[31]:
```
df.iloc[1:3, :]
```

[31]:
```
                   A         B         C         D
2013-01-02 -0.641384  0.495139 -2.020046  0.001336
2013-01-03  2.294530 -0.635708 -0.733891 -0.496177
```

For slicing columns explicitly:

[32]:
```
df.iloc[:, 1:3]
```

[32]:
```
                   B         C
2013-01-01 -1.909945 -0.479259
2013-01-02  0.495139 -2.020046
2013-01-03 -0.635708 -0.733891
2013-01-04 -0.463833  0.509944
2013-01-05 -0.302788  0.607642
2013-01-06 -0.186075 -1.822979
```

For getting a value explicitly:

[33]:
```
df.iloc[1, 1]
```

[33]:
```
0.49513879986688225
```

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

[34]:
```
df.iat[1, 1]
```

[34]: 0.49513879986688225

1.3.4 Boolean Indexing

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

[35]:
```
df[df > 0]
```

[35]:

	A	B	C	D
2013-01-01	0.603855	NaN	NaN	1.702171
2013-01-02	NaN	0.495139	NaN	0.001336
2013-01-03	2.294530	NaN	NaN	NaN
2013-01-04	NaN	NaN	0.509944	0.435204
2013-01-05	NaN	NaN	0.607642	NaN
2013-01-06	0.738407	NaN	NaN	0.718949

Using the isin() method for filtering:

[36]:
```
df2 = df.copy()
df2['E'] = ['one', 'one', 'two', 'three', 'four', 'three']
df2
```

[36]:

	A	B	C	D	E
2013-01-01	0.603855	-1.909945	-0.479259	1.702171	one
2013-01-02	-0.641384	0.495139	-2.020046	0.001336	one
2013-01-03	2.294530	-0.635708	-0.733891	-0.496177	two
2013-01-04	-0.640988	-0.463833	0.509944	0.435204	three
2013-01-05	-2.107043	-0.302788	0.607642	-0.051413	four
2013-01-06	0.738407	-0.186075	-1.822979	0.718949	three

[37]:
```
df2[df2['E'].isin(['two', 'four'])]
```

[37]:

	A	B	C	D	E
2013-01-03	2.294530	-0.635708	-0.733891	-0.496177	two
2013-01-05	-2.107043	-0.302788	0.607642	-0.051413	four

1.3.5 Setting

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

[38]:
```
s1 = pd.Series([1, 2, 3, 4, 5, 6], index=pd.date_range('20130102', periods=6))
s1
```

[38]:
```
2013-01-02    1
2013-01-03    2
2013-01-04    3
2013-01-05    4
2013-01-06    5
2013-01-07    6
Freq: D, dtype: int64
```

[39]:
```python
df['F'] = s1
```

Setting values by label:

[40]:
```python
df.at[dates[0], 'A'] = 0
```

Setting values by position:

[41]:
```python
df.iat[0, 1] = 0
```

Setting by assigning with a NumPy array:

[42]:
```python
df.loc[:, 'D'] = np.array([5] * len(df))
```

The result of the prior setting operations.

[43]:
```python
df
```

[43]:

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-0.479259	5	NaN
2013-01-02	-0.641384	0.495139	-2.020046	5	1.0
2013-01-03	2.294530	-0.635708	-0.733891	5	2.0
2013-01-04	-0.640988	-0.463833	0.509944	5	3.0
2013-01-05	-2.107043	-0.302788	0.607642	5	4.0
2013-01-06	0.738407	-0.186075	-1.822979	5	5.0

A where operation with setting.

[44]:
```python
df2 = df.copy()

df2[df2 > 0] = -df2

df2
```

[44]:

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-0.479259	-5	NaN
2013-01-02	-0.641384	-0.495139	-2.020046	-5	-1.0
2013-01-03	-2.294530	-0.635708	-0.733891	-5	-2.0
2013-01-04	-0.640988	-0.463833	-0.509944	-5	-3.0
2013-01-05	-2.107043	-0.302788	-0.607642	-5	-4.0
2013-01-06	-0.738407	-0.186075	-1.822979	-5	-5.0

1.3.6 Missing Data

pandas primarily uses the value np.nan to represent missing data. It is by default not included in computations. See the Missing Data section.

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

[45]:
```
df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])

df1.loc[dates[0]:dates[1], 'E'] = 1

df1
```

[45]:

	A	B	C	D	F	E
2013-01-01	0.000000	0.000000	-0.479259	5	NaN	1.0
2013-01-02	-0.641384	0.495139	-2.020046	5	1.0	1.0
2013-01-03	2.294530	-0.635708	-0.733891	5	2.0	NaN
2013-01-04	-0.640988	-0.463833	0.509944	5	3.0	NaN

** To drop any rows that have missing data. **

[46]:
```
df1.dropna()
```

[46]:

	A	B	C	D	F	E
2013-01-02	-0.641384	0.495139	-2.020046	5	1.0	1.0

Filling missing data.

[47]:
```
df1.fillna(value=5)
```

[47]:

	A	B	C	D	F	E
2013-01-01	0.000000	0.000000	-0.479259	5	5.0	1.0
2013-01-02	-0.641384	0.495139	-2.020046	5	1.0	1.0
2013-01-03	2.294530	-0.635708	-0.733891	5	2.0	5.0
2013-01-04	-0.640988	-0.463833	0.509944	5	3.0	5.0

To get the boolean mask where values are nan

[48]:
```
df1.isnull()
```

[48]:

	A	B	C	D	F	E
2013-01-01	False	False	False	False	True	False
2013-01-02	False	False	False	False	False	False
2013-01-03	False	False	False	False	False	True
2013-01-04	False	False	False	False	False	True

1.4 Operations

1.4.1 Stats

Performing a descriptive statistic:

[49]:
```
df.mean()
```

[49]:
```
A   -0.059413
B   -0.182211
C   -0.656432
D    5.000000
F    3.000000
dtype: float64
```

Same operation on the other axis:

[50]:
```
df.mean(1)
```

[50]:
```
2013-01-01    1.130185
2013-01-02    0.766742
2013-01-03    1.584986
2013-01-04    1.481025
2013-01-05    1.439562
2013-01-06    1.745871
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

[51]:
```
s = pd.Series([1, 3, 5, np.nan, 6, 8], index=dates).shift(2)
s
```

[51]:
```
2013-01-01    NaN
2013-01-02    NaN
2013-01-03    1.0
2013-01-04    3.0
2013-01-05    5.0
2013-01-06    NaN
Freq: D, dtype: float64
```

[52]:
```
df.sub(s, axis='index')
```

[52]:
```
                   A         B         C    D    F
2013-01-01       NaN       NaN       NaN  NaN  NaN
2013-01-02       NaN       NaN       NaN  NaN  NaN
2013-01-03  1.294530 -1.635708 -1.733891  4.0  1.0
2013-01-04 -3.640988 -3.463833 -2.490056  2.0  0.0
```

```
2013-01-05 -7.107043 -5.302788 -4.392358  0.0 -1.0
2013-01-06       NaN       NaN       NaN  NaN  NaN
```

1.4.2 Apply

Applying functions to the data:

[53]:
```
df.apply(np.cumsum)
```

[53]:
```
                   A         B         C   D     F
2013-01-01  0.000000  0.000000 -0.479259   5   NaN
2013-01-02 -0.641384  0.495139 -2.499305  10   1.0
2013-01-03  1.653146 -0.140569 -3.233196  15   3.0
2013-01-04  1.012158 -0.604402 -2.723252  20   6.0
2013-01-05 -1.094885 -0.907190 -2.115610  25  10.0
2013-01-06 -0.356479 -1.093264 -3.938589  30  15.0
```

1.4.3 Histrogramming

[54]:
```
s = pd.Series(np.random.randint(0, 7, size=10))
s
```

[54]:
```
0    0
1    1
2    0
3    2
4    6
5    0
6    5
7    4
8    2
9    5
dtype: int64
```

[55]:
```
s.value_counts()
```

[55]:
```
0    3
2    2
5    2
1    1
4    1
6    1
dtype: int64
```

1.4.4 String Method

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).

[56]:
```
s = pd.Series(['A', 'B', 'C', 'AaBa', 'Baca', np.nan, 'CABA', 'dog', 'cat'])
s
```

[56]:
```
0       A
1       B
2       C
3    AaBa
4    Baca
5     NaN
6    CABA
7     dog
8     cat
dtype: object
```

[57]:
```
s.str.lower()
```

[57]:
```
0       a
1       b
2       c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

1.5 Merge

1.5.1 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():

[58]:
```
df = pd.DataFrame(np.random.randn(10, 4))
df
```

[58]:
```
          0         1         2         3
0  0.380325 -0.880526 -1.176924 -0.179586
1  0.291227  1.116187  0.554469 -0.492768
2  1.699139 -0.608916 -0.704861 -0.863620
3 -0.248738 -1.029515  0.091007 -1.283921
4  0.927656  0.290976 -0.133193 -0.841017
5  0.244215 -0.564498  1.555279 -0.878605
6 -1.048047  0.210264 -0.961586 -1.593050
7 -0.697241 -1.359378  1.545611 -1.927015
8 -0.854028 -0.163953 -0.129962  0.004403
9  0.245984  0.800387  0.304697  1.477378
```

[59]:
```python
# Break it into pieces
pieces = [df[0:3], df[7:]]
pd.concat(pieces)
```

[59]:
```
          0         1         2         3
0  0.380325 -0.880526 -1.176924 -0.179586
1  0.291227  1.116187  0.554469 -0.492768
2  1.699139 -0.608916 -0.704861 -0.863620
7 -0.697241 -1.359378  1.545611 -1.927015
8 -0.854028 -0.163953 -0.129962  0.004403
9  0.245984  0.800387  0.304697  1.477378
```

1.5.2 Join

SQL style merges

[60]:
```python
left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})
right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})

pd.merge(left, right, on='key')
```

[60]:
```
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

Another Example:

[61]:
```python
left = pd.DataFrame({'key': ['foo', 'bar'], 'lval': [1, 2]})
right = pd.DataFrame({'key': ['foo', 'bar'], 'rval': [4, 5]})

pd.merge(left, right, on='key')
```

[61]:
```
   key  lval  rval
0  foo     1     4
1  bar     2     5
```

1.5.3 Append

Append rows to a dataframe.

[62]:
```python
df = pd.DataFrame(np.random.randn(8, 4), columns=['A', 'B', 'C', 'D'])
df
```

[62]:
```
          A         B         C         D
0 -1.001153 -1.814441 -1.520158 -2.048174
1  0.265521 -0.123103 -0.742055  1.244682
2 -0.268542  0.870505  0.368634  0.151854
3  0.411732  1.915521 -0.064925  0.169919
4  1.173807  0.788658 -0.096123 -0.847175
5 -0.841019  1.071743  0.744012  0.071097
6  0.358983 -1.069872 -1.282452  1.333018
7 -0.314903  0.507522 -1.372580 -0.060064
```

[63]:
```python
s = df.iloc[3]
df.append(s, ignore_index=True)
```

[63]:
```
          A         B         C         D
0 -1.001153 -1.814441 -1.520158 -2.048174
1  0.265521 -0.123103 -0.742055  1.244682
2 -0.268542  0.870505  0.368634  0.151854
3  0.411732  1.915521 -0.064925  0.169919
4  1.173807  0.788658 -0.096123 -0.847175
5 -0.841019  1.071743  0.744012  0.071097
6  0.358983 -1.069872 -1.282452  1.333018
7 -0.314903  0.507522 -1.372580 -0.060064
8  0.411732  1.915521 -0.064925  0.169919
```

1.6 Grouping

By "group by" we are referring to a process involving one or 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

[64]:
```python
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
```

[64]:
```
     A      B         C         D
0  foo    one -0.849853  0.919800
1  bar    one -0.993119  0.490020
2  foo    two -0.737876  1.086789
3  bar  three  1.388501 -0.697871
4  foo    two -0.172797 -1.672252
5  bar    two  1.190397 -1.379797
6  foo    one -0.031296 -1.438906
7  foo  three -1.978317 -0.555656
```

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

[65]:
```
df.groupby('A').sum()
```

[65]:
```
            C         D
A
bar  1.585779 -1.587649
foo -3.770139 -1.660224
```

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

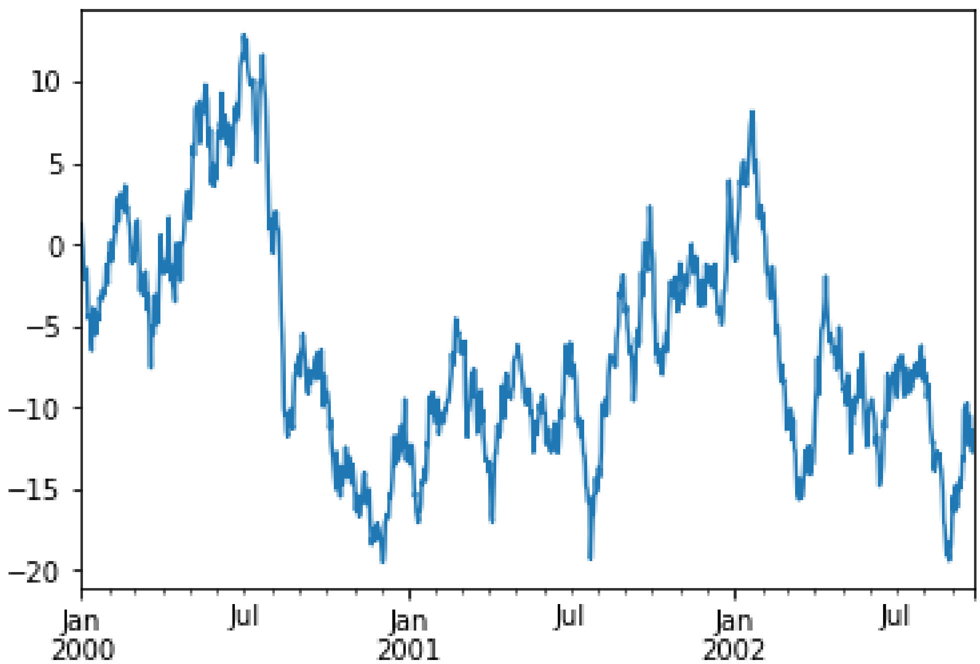
[66]:
```
df.groupby(['A', 'B']).sum()
```

[66]:
```
                  C         D
A   B
bar one   -0.993119  0.490020
    three  1.388501 -0.697871
    two    1.190397 -1.379797
foo one   -0.881148 -0.519107
    three -1.978317 -0.555656
    two   -0.910673 -0.585462
```

1.7 Plotting

[67]:
```
ts = pd.Series(np.random.randn(1000),
                index=pd.date_range('1/1/2000', periods=1000))
ts = ts.cumsum()
ts.plot()
```

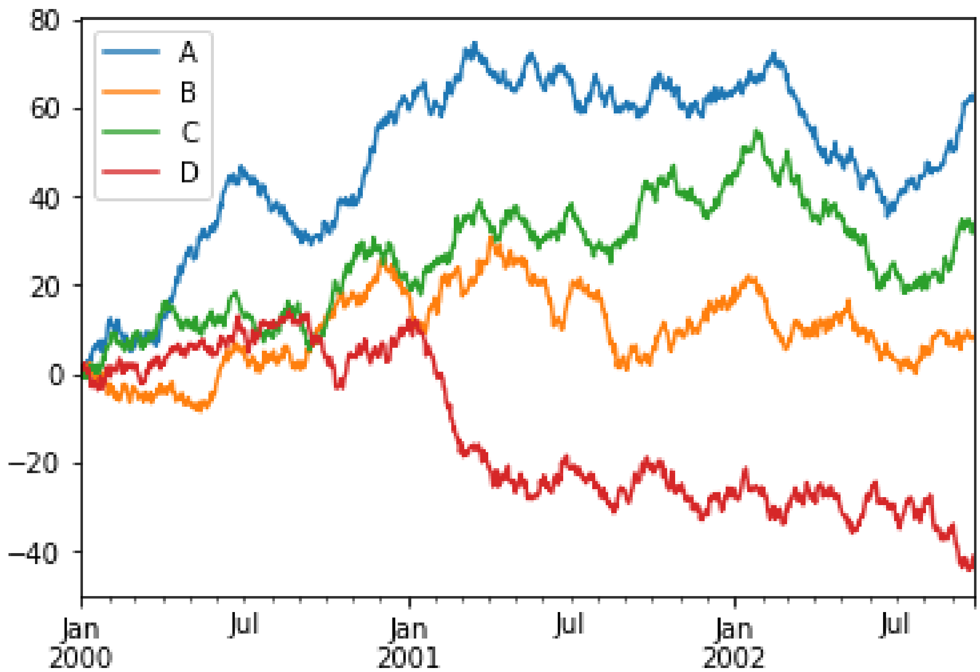
[67]:
```
<AxesSubplot:>
```



[68]:
```
df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
                  columns=['A', 'B', 'C', 'D'])
df = df.cumsum()

df.plot()
```

[68]: <AxesSubplot:>



1.8 Getting data in/out

1.8.1 CSV

[69]:
```
df.to_csv('foo.csv')
```

[70]:
```
pd.read_csv('foo.csv').head()
```

[70]:

	Unnamed: 0	A	B	C	D
0	2000-01-01	-0.449357	0.845010	0.597582	0.693725
1	2000-01-02	-0.977990	0.857001	-0.033241	1.039799
2	2000-01-03	0.051343	0.851306	-0.088908	1.869627
3	2000-01-04	0.033648	0.792420	-0.969570	1.940509
4	2000-01-05	1.813600	1.798851	1.178586	2.378155