In [ ]:

HW 0 - Intro to Pandas

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

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib as plt
```

Object Creation

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

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

Out[3]:
```
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:

In [4]:
```
dates = pd.date_range('20130101', periods=6)
dates
```

Out[4]:
```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')
```

In [5]:
```
df = pd.DataFrame(np.random.randn(6, 4), index=dates, columns=list('ABCD'))
df
```

Out[5]:

	A	B	C	D
2013-01-01	-1.056100	-1.476868	-0.295436	1.166565
2013-01-02	-1.121601	0.121268	-0.425511	0.824180
2013-01-03	0.767924	-1.546357	-0.603759	2.138908
2013-01-04	0.956205	1.249681	0.080045	-0.310805
2013-01-05	-0.964825	0.302828	-1.094715	-0.617747
2013-01-06	0.000513	1.469778	1.011251	-0.198495

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

In [6]:
```
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
```

Out[6]:

	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.

In [7]:
```
df2.dtypes
```

Out[7]:
```
A           float64
B    datetime64[ns]
C           float32
D             int32
E          category
F            object
dtype: object
```

Viewing Data

View the top and bottom rows of the frame:

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

Out[8]:

	A	B	C	D
2013-01-01	-1.056100	-1.476868	-0.295436	1.166565
2013-01-02	-1.121601	0.121268	-0.425511	0.824180
2013-01-03	0.767924	-1.546357	-0.603759	2.138908
2013-01-04	0.956205	1.249681	0.080045	-0.310805
2013-01-05	-0.964825	0.302828	-1.094715	-0.617747

In [9]:
```
df.tail(3)
```

Out[9]:

	A	B	C	D
2013-01-04	0.956205	1.249681	0.080045	-0.310805
2013-01-05	-0.964825	0.302828	-1.094715	-0.617747
2013-01-06	0.000513	1.469778	1.011251	-0.198495

Display the index, columns:

```
In [10]: df.index
```

```
Out[10]: DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
                        '2013-01-05', '2013-01-06'],
                       dtype='datetime64[ns]', freq='D')
```

```
In [11]: df.columns
```

```
Out[11]: 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.

```
In [12]: df.values
```

```
Out[12]: array([[-1.05610049e+00, -1.47686848e+00, -2.95436136e-01,
                  1.16656466e+00],
                [-1.12160062e+00,  1.21268178e-01, -4.25511032e-01,
                  8.24179787e-01],
                [ 7.67924032e-01, -1.54635681e+00, -6.03758588e-01,
                  2.13890800e+00],
                [ 9.56204814e-01,  1.24968056e+00,  8.00451627e-02,
                 -3.10804594e-01],
                [-9.64824934e-01,  3.02827964e-01, -1.09471513e+00,
                 -6.17746952e-01],
                [ 5.13010757e-04,  1.46977787e+00,  1.01125091e+00,
                 -1.98495321e-01]])
```

```
In [13]: df2.values
```

```
Out[13]: 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:

In [14]:
```
df.describe()
```

Out[14]:

	A	B	C	D
count	6.000000	6.000000	6.000000	6.000000
mean	-0.236314	0.020055	-0.221354	0.500434
std	0.945853	1.296017	0.716424	1.061139
min	-1.121601	-1.546357	-1.094715	-0.617747
25%	-1.033282	-1.077334	-0.559197	-0.282727
50%	-0.482156	0.212048	-0.360474	0.312842
75%	0.576071	1.012967	-0.013825	1.080968
max	0.956205	1.469778	1.011251	2.138908

Transposing your data:

In [15]:
```
df.T
```

Out[15]:

	2013-01-01	2013-01-02	2013-01-03	2013-01-04	2013-01-05	2013-01-06
A	-1.056100	-1.121601	0.767924	0.956205	-0.964825	0.000513
B	-1.476868	0.121268	-1.546357	1.249681	0.302828	1.469778
C	-0.295436	-0.425511	-0.603759	0.080045	-1.094715	1.011251
D	1.166565	0.824180	2.138908	-0.310805	-0.617747	-0.198495

Sorting by an axis:

In [16]:
```
df.sort_index(axis=1, ascending=False)
```

Out[16]:

	D	C	B	A
2013-01-01	1.166565	-0.295436	-1.476868	-1.056100
2013-01-02	0.824180	-0.425511	0.121268	-1.121601
2013-01-03	2.138908	-0.603759	-1.546357	0.767924
2013-01-04	-0.310805	0.080045	1.249681	0.956205
2013-01-05	-0.617747	-1.094715	0.302828	-0.964825
2013-01-06	-0.198495	1.011251	1.469778	0.000513

Sorting by values:

In [17]:
```
df.sort_values(by='B')
```

Out[17]:

	A	B	C	D
2013-01-03	0.767924	-1.546357	-0.603759	2.138908
2013-01-01	-1.056100	-1.476868	-0.295436	1.166565
2013-01-02	-1.121601	0.121268	-0.425511	0.824180
2013-01-05	-0.964825	0.302828	-1.094715	-0.617747
2013-01-04	0.956205	1.249681	0.080045	-0.310805
2013-01-06	0.000513	1.469778	1.011251	-0.198495

Selection

Getting

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

In [18]:
```
df['A']
```

Out[18]:
```
2013-01-01   -1.056100
2013-01-02   -1.121601
2013-01-03    0.767924
2013-01-04    0.956205
2013-01-05   -0.964825
2013-01-06    0.000513
Freq: D, Name: A, dtype: float64
```

Selecting via [ ], which slices the rows.

In [19]:
```
df[0:3]
```

Out[19]:

	A	B	C	D
2013-01-01	-1.056100	-1.476868	-0.295436	1.166565
2013-01-02	-1.121601	0.121268	-0.425511	0.824180
2013-01-03	0.767924	-1.546357	-0.603759	2.138908

In [20]:
```
df['20130102':'20130104']
```

Out[20]:

	A	B	C	D
2013-01-02	-1.121601	0.121268	-0.425511	0.824180
2013-01-03	0.767924	-1.546357	-0.603759	2.138908
2013-01-04	0.956205	1.249681	0.080045	-0.310805

Selection by label

For getting a cross section using a label:

In [21]:
```
df.loc[dates[0]]
```

Out[21]:
```
A   -1.056100
B   -1.476868
C   -0.295436
D    1.166565
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label:

In [22]:
```
df.loc[:, ['A', 'B']]
```

Out[22]:

	A	B
2013-01-01	-1.056100	-1.476868
2013-01-02	-1.121601	0.121268
2013-01-03	0.767924	-1.546357
2013-01-04	0.956205	1.249681
2013-01-05	-0.964825	0.302828
2013-01-06	0.000513	1.469778

Showing label slicing, both endpoints are included:

In [23]:
```
df.loc['20130102':'20130104', ['A', 'B']]
```

Out[23]:

	A	B
2013-01-02	-1.121601	0.121268
2013-01-03	0.767924	-1.546357
2013-01-04	0.956205	1.249681

Reduction in the dimensions of the returned object:

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

Out[24]:
```
A   -1.121601
B    0.121268
Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value:

In [25]:
```
df.loc[dates[0], 'A']
```

Out[25]:
```
-1.0561004945487016
```

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

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

Out[26]:
```
-1.0561004945487016
```

Selection by position

Select via the position of the passed integers:

In [27]:
```
df.iloc[3]
```

Out[27]:
```
A    0.956205
B    1.249681
C    0.080045
D   -0.310805
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python:

In [28]:
```
df.iloc[3:5, 0:2]
```

Out[28]:

	A	B
2013-01-04	0.956205	1.249681
2013-01-05	-0.964825	0.302828

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

In [29]:
```
df.iloc[[1, 2, 4], [0, 2]]
```

Out[29]:

	A	C
2013-01-02	-1.121601	-0.425511
2013-01-03	0.767924	-0.603759
2013-01-05	-0.964825	-1.094715

For slicing rows explicitly:

In [30]:
```
df.iloc[1:3, :]
```

Out[30]:

	A	B	C	D
2013-01-02	-1.121601	0.121268	-0.425511	0.824180
2013-01-03	0.767924	-1.546357	-0.603759	2.138908

For slicing columns explicitly:

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

Out[31]:

	B	C
2013-01-01	-1.476868	-0.295436
2013-01-02	0.121268	-0.425511
2013-01-03	-1.546357	-0.603759
2013-01-04	1.249681	0.080045
2013-01-05	0.302828	-1.094715
2013-01-06	1.469778	1.011251

For getting a value explicitly:

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

Out[32]:
```
0.12126817754342496
```

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

In [33]:
```
df.iat[1, 1]
```

Out[33]:
```
0.12126817754342496
```

Boolean Indexing

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

In [34]:
```
df[df > 0]
```

Out[34]:

	A	B	C	D
2013-01-01	NaN	NaN	NaN	1.166565
2013-01-02	NaN	0.121268	NaN	0.824180
2013-01-03	0.767924	NaN	NaN	2.138908
2013-01-04	0.956205	1.249681	0.080045	NaN
2013-01-05	NaN	0.302828	NaN	NaN
2013-01-06	0.000513	1.469778	1.011251	NaN

Using the isin() method for filtering:

In [35]:
```
df2 = df.copy()
df2['E'] = ['one', 'one', 'two', 'three', 'four', 'three']
df2
```

Out[35]:

	A	B	C	D	E
2013-01-01	-1.056100	-1.476868	-0.295436	1.166565	one
2013-01-02	-1.121601	0.121268	-0.425511	0.824180	one
2013-01-03	0.767924	-1.546357	-0.603759	2.138908	two
2013-01-04	0.956205	1.249681	0.080045	-0.310805	three
2013-01-05	-0.964825	0.302828	-1.094715	-0.617747	four
2013-01-06	0.000513	1.469778	1.011251	-0.198495	three

In [36]:
```
df2[df2['E'].isin(['two', 'four'])]
```

Out[36]:

	A	B	C	D	E
2013-01-03	0.767924	-1.546357	-0.603759	2.138908	two
2013-01-05	-0.964825	0.302828	-1.094715	-0.617747	four

Setting

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

In [37]:
```
s1 = pd.Series([1, 2, 3, 4, 5, 6], index=pd.date_range('20130102', periods=6))
s1
```

Out[37]:
```
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
```

In [38]:
```
df['F'] = s1
```

Setting values by label:

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

Setting values by position:

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

Setting by assigning with a NumPy array:

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

The result of the prior setting operations.

In [43]:
```
df
```

Out[43]:

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-0.295436	5	NaN
2013-01-02	-1.121601	0.121268	-0.425511	5	1.0
2013-01-03	0.767924	-1.546357	-0.603759	5	2.0
2013-01-04	0.956205	1.249681	0.080045	5	3.0
2013-01-05	-0.964825	0.302828	-1.094715	5	4.0
2013-01-06	0.000513	1.469778	1.011251	5	5.0

A where operation with setting.

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

df2[df2 > 0] = -df2

df2
```

Out[44]:

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-0.295436	-5	NaN
2013-01-02	-1.121601	-0.121268	-0.425511	-5	-1.0
2013-01-03	-0.767924	-1.546357	-0.603759	-5	-2.0
2013-01-04	-0.956205	-1.249681	-0.080045	-5	-3.0
2013-01-05	-0.964825	-0.302828	-1.094715	-5	-4.0
2013-01-06	-0.000513	-1.469778	-1.011251	-5	-5.0

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.

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

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

df1
```

Out[45]:

	A	B	C	D	F	E
2013-01-01	0.000000	0.000000	-0.295436	5	NaN	1.0
2013-01-02	-1.121601	0.121268	-0.425511	5	1.0	1.0
2013-01-03	0.767924	-1.546357	-0.603759	5	2.0	NaN
2013-01-04	0.956205	1.249681	0.080045	5	3.0	NaN

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

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

Out[46]:

	A	B	C	D	F	E
2013-01-02	-1.121601	0.121268	-0.425511	5	1.0	1.0

Filling missing data.

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

Out[47]:

	A	B	C	D	F	E
2013-01-01	0.000000	0.000000	-0.295436	5	5.0	1.0
2013-01-02	-1.121601	0.121268	-0.425511	5	1.0	1.0
2013-01-03	0.767924	-1.546357	-0.603759	5	2.0	5.0
2013-01-04	0.956205	1.249681	0.080045	5	3.0	5.0

To get the boolean mask where values are nan

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

Out[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

Operations

Stats

Performing a descriptive statistic:

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

Out[49]:
```
A   -0.060297
B    0.266200
C   -0.221354
D    5.000000
F    3.000000
dtype: float64
```

Same operation on the other axis:

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

Out[50]:
```
2013-01-01    1.176141
2013-01-02    0.914831
2013-01-03    1.123562
2013-01-04    2.057186
2013-01-05    1.448658
2013-01-06    2.496308
Freq: D, dtype: float64
```

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

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

Out[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
```

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

Out[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	-0.232076	-2.546357	-1.603759	4.0	1.0
2013-01-04	-2.043795	-1.750319	-2.919955	2.0	0.0
2013-01-05	-5.964825	-4.697172	-6.094715	0.0	-1.0
2013-01-06	NaN	NaN	NaN	NaN	NaN

Apply

Applying functions to the data:

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

Out[53]:

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-0.295436	5	NaN
2013-01-02	-1.121601	0.121268	-0.720947	10	1.0
2013-01-03	-0.353677	-1.425089	-1.324706	15	3.0
2013-01-04	0.602528	-0.175408	-1.244661	20	6.0
2013-01-05	-0.362297	0.127420	-2.339376	25	10.0
2013-01-06	-0.361784	1.597198	-1.328125	30	15.0

Histrogramming

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

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

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

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

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).

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

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

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

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

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():

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

Out[58]:

	0	1	2	3
0	0.900760	-0.259718	0.428272	-0.760726
1	0.862023	-2.158267	0.103809	-0.396985
2	0.759961	-0.973911	0.715707	-0.594566
3	0.127674	0.003954	-0.422543	-0.375582
4	0.964910	2.627521	0.636512	-0.356865
5	-1.067098	0.095595	1.182397	-1.015380
6	-1.955458	0.214194	0.344601	-0.157795
7	-1.571254	-0.588933	-1.051022	1.081947
8	-0.183701	0.037992	0.228459	-0.464717
9	-0.390389	-1.373987	-0.004915	0.429512

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

Out[59]:

	0	1	2	3
0	0.900760	-0.259718	0.428272	-0.760726
1	0.862023	-2.158267	0.103809	-0.396985
2	0.759961	-0.973911	0.715707	-0.594566
7	-1.571254	-0.588933	-1.051022	1.081947
8	-0.183701	0.037992	0.228459	-0.464717
9	-0.390389	-1.373987	-0.004915	0.429512

Join

SQL style merges

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

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

Out[60]:

	key	lval	rval
0	foo	1	4
1	foo	1	5
2	foo	2	4
3	foo	2	5

Another Example:

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

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

Out[61]:

	key	lval	rval
0	foo	1	4
1	bar	2	5

Append

Append rows to a dataframe.

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

Out[62]:

	A	B	C	D
0	0.391050	-0.144900	-0.242960	0.961968
1	-0.161318	0.149084	-0.816692	1.081439
2	-0.161265	0.874178	0.605855	0.520845
3	1.355729	-0.174194	-2.494256	-0.947909
4	-0.362028	0.442370	-0.663817	-0.981738
5	-0.535374	-0.023833	1.412833	1.378778
6	0.809874	-0.225264	-0.697647	0.488746
7	0.313075	0.890311	-1.415258	1.226300

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

Out[63]:

	A	B	C	D
0	0.391050	-0.144900	-0.242960	0.961968
1	-0.161318	0.149084	-0.816692	1.081439
2	-0.161265	0.874178	0.605855	0.520845
3	1.355729	-0.174194	-2.494256	-0.947909
4	-0.362028	0.442370	-0.663817	-0.981738
5	-0.535374	-0.023833	1.412833	1.378778
6	0.809874	-0.225264	-0.697647	0.488746
7	0.313075	0.890311	-1.415258	1.226300
8	1.355729	-0.174194	-2.494256	-0.947909

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

In [64]:
```
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
```

Out[64]:

	A	B	C	D
0	foo	one	-0.454244	-0.829323
1	bar	one	0.101498	0.040118
2	foo	two	1.061406	-0.066974
3	bar	three	-0.354196	-0.953839
4	foo	two	-0.472186	1.744688
5	bar	two	0.770577	1.004619
6	foo	one	0.183964	-2.351791
7	foo	three	0.793412	-0.900062

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

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

Out[65]:

	C	D
A		
bar	0.517879	0.090898
foo	1.112352	-2.403462

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

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

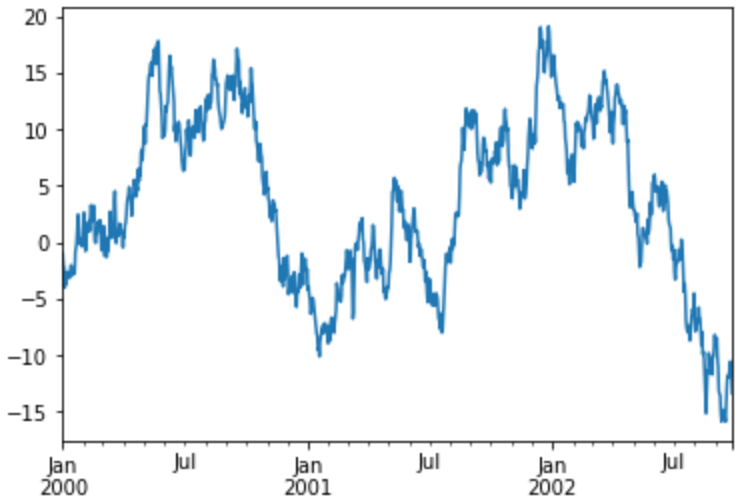
Out[66]:

A	B	C	D
bar	one	0.101498	0.040118
	three	-0.354196	-0.953839
	two	0.770577	1.004619
foo	one	-0.270280	-3.181114
	three	0.793412	-0.900062
	two	0.589220	1.677714

Plotting

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

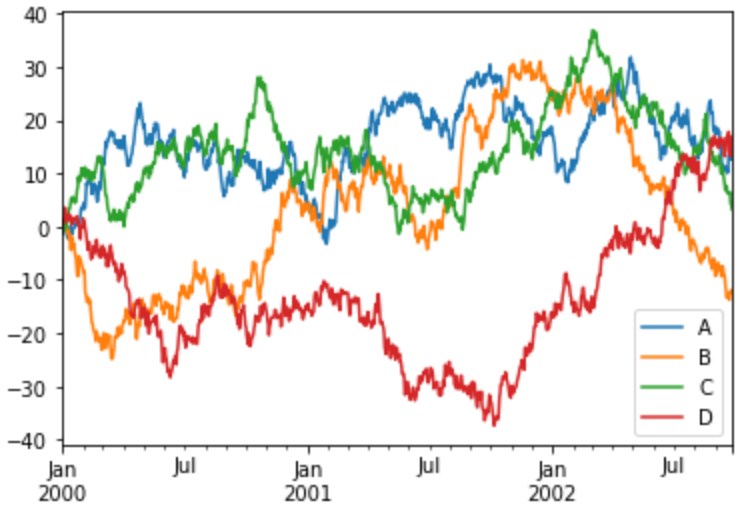
Out[67]: <AxesSubplot:>



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

df.plot()
```

Out[68]: <AxesSubplot:>



Getting data in/out

CSV

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

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

Out[70]:

	Unnamed: 0	A	B	C	D
0	2000-01-01	-1.297515	0.618083	1.148721	0.363292
1	2000-01-02	1.410537	0.210274	0.519842	1.116732
2	2000-01-03	0.902020	-0.380802	-0.482574	0.639611
3	2000-01-04	0.052136	-0.548020	-0.737682	1.478004
4	2000-01-05	-0.380147	1.053637	-0.314097	3.582150

In [ ]: