Python 3x Programing

Lesson PANDAS

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Time 90 mins

Content

Introduction to Pandas

Python Pandas

- Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. The name Pandas is derived from the word Panel Data – an Econometrics from Multidimensional data.
- To use Pandas, must import pandas as pd
- Pandas deals with the following three data structures
  - Series: dimension = 1
  - DataFrame: dimension = 2
  - Panel: dimension = 3

- Fast and efficient DataFrame object with default and customized indexing.
- Tools for loading data into in-memory data objects from different file formats.
- Data alignment and integrated handling of missing data.
- Reshaping and pivoting of date sets.
- Label-based slicing, indexing and subsetting of large data sets.
- Columns from a data structure can be deleted or inserted.
- Group by data for aggregation and transformations.
- High performance merging and joining of data.
- Time Series functionality.

Python Pandas - Series

- Create: **pandas.Series(data, index, dtype, copy)**
  - **Data:** data takes various forms like ndarray, list, constants
  - **Index:** Index values must be unique and hashable, same length as data. Default np.arrange(n) if no index is passed.
  - **Dtype:** dtype is for data type. If None, data type will be inferred
  - **Copy:** Copy data. Default False

```
#import the pandas library and aliasing as pd
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data)
print(s)
```

```
0    a
1    b
2    c
3    d
```

- Retrieve Data Using Label

```
import pandas as pd
s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])

#retrieve a single element

print (s[0])
print (s['a'])
print(s[1:5])
```

→

```
1
1
b    2
c    3
d    4
e    5
```

Python Pandas - DataFrame

- **Create**:
- pandas.DataFrame(data, index, columns, dtype, copy)
- Columns: For column labels, the optional default syntax is - np.arrange(n). This is only true if no index is passed.

- Creating dataframe many ways
- Adding column
- Delete column
- Row Selection, Addition, and Deletion

Example – Create Dataframe

```
import pandas as pd
data = [1,2,3,4,5]
df = pd.DataFrame(data)
print(df)

print('More dataframe example')

data = [['Alex',10],['Bob',12],['Clarke',13]]
df1 = pd.DataFrame(data,columns=['Name','Age'])
print (df1)

data = {'Name':['Tom', 'Jack', 'Steve', 'Ricky'],'Age':[28,34,29,42]}
df2 = pd.DataFrame(data)
print (df2)

data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]
df3 = pd.DataFrame(data)
print(df3)

data = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df4 = pd.DataFrame(data)
print(df4)
```

```
   0
0  1
1  2
2  3
3  4
4  5
More dataframe example
     Name  Age
0    Alex   10
1     Bob   12
2  Clarke   13
   Age   Name
0   28    Tom
1   34   Jack
2   29  Steve
3   42  Ricky
   a   b     c
0  1   2   NaN
1  5  10  20.0
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
```

Column Addition

```python
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
     'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)

# Adding a new column to an existing DataFrame object with c
    passing new series

print ("Adding a new column by passing as Series:")
df['three']=pd.Series([10,20,30],index=['a','b','c'])
print df

print ("Adding a new column using the existing columns in DataFrame:")
df['four']=df['one']+df['three']

print (df)
```

```
Adding a new column by passing as Series:
   one  two  three
a  1.0    1   10.0
b  2.0    2   20.0
c  3.0    3   30.0
d  NaN    4    NaN
Adding a new column using the existing columns in DataFrame:
   one  two  three  four
a  1.0    1   10.0  11.0
b  2.0    2   20.0  22.0
c  3.0    3   30.0  33.0
d  NaN    4    NaN   NaN
```

Column Deletion

```python
# Using the previous DataFrame, we will delete a column
# using del function
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
     'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd']),
     'three' : pd.Series([10,20,30], index=['a','b','c'])}

df = pd.DataFrame(d)
print ("Our dataframe is:")
print df

# using del function
print ("Deleting the first column using DEL function:")
del df['one']
print df

# using pop function
print ("Deleting another column using POP function:")
df.pop('two')
print df
```

```
Our dataframe is:
   one  three  two
a  1.0   10.0    1
b  2.0   20.0    2
c  3.0   30.0    3
d  NaN    NaN    4
Deleting the first column using DEL function:
   three  two
a   10.0    1
b   20.0    2
c   30.0    3
d    NaN    4
Deleting another column using POP function:
   three
a   10.0
b   20.0
c   30.0
d    NaN
```

Row Selection, Addition, and Deletion

```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
     'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)

print(df)

print('Selection by Label')
print (df.loc['b'])

print('Selection by Label')
print(df.iloc[2])

print('Slice Rows')
print (df[2:4])

print('Addition of Rows')
df2 = pd.DataFrame([[5, 6], [7, 8]], columns = ['a','b'])
df = df.append(df2)
print(df)

print('Drop rows with label ....')
df = df.drop(0)
df = df.drop('d')
df = df.drop('c')
df = df.drop(1)
print (df)
```

```
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
Selection by Label
one    2.0
two    2.0
Name: b, dtype: float64
Selection by Label
one    3.0
two    3.0
Name: c, dtype: float64
Slice Rows
   one  two
c  3.0    3
d  NaN    4
Addition of Rows
     a    b  one  two
a  NaN  NaN  1.0  1.0
b  NaN  NaN  2.0  2.0
c  NaN  NaN  3.0  3.0
d  NaN  NaN  NaN  4.0
0  5.0  6.0  NaN  NaN
1  7.0  8.0  NaN  NaN
Drop rows with label ....
    a   b  one  two
a NaN NaN  1.0  1.0
b NaN NaN  2.0  2.0
```

Python Pandas - Panel

- Create: **pandas.Panel(data, items, major_axis, minor_axis, dtype, copy)**
- Data: Data takes various forms like ndarray, series, map, lists, dict, constants and also another DataFrame
- Items: axis=0
- Major_axis: axis=1
- Minor_axis: axis=2
- Dtype: Data type of each column
- Copy: Copy data. Default, false

```
# creating an empty panel
import pandas as pd
import numpy as np

data = np.random.rand(2,4,5)
p = pd.Panel(data)
print(p)
```

```
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 5 (minor_axis)
Items axis: 0 to 1
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 4
```

Example - From 3D ndarray

```python
# creating an empty panel
import pandas as pd
import numpy as np
data = {'Item1' : pd.DataFrame(np.random.randn(4, 3)),
   'Item2' : pd.DataFrame(np.random.randn(4, 2))}

p = pd.Panel(data)

print(p)

print (p['Item1'])
print (p['Item2'])
```

```
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
          0         1         2
0  0.386301  0.937950  1.331670
1 -0.838045 -0.758695 -1.086383
2  0.278756 -0.402047  1.628165
3  0.673774 -0.432396  0.485400
          0         1   2
0  0.654729  0.836816 NaN
1 -0.010171  2.285872 NaN
2 -0.013479 -1.614701 NaN
3 -0.431427  1.147201 NaN
```

Series Basic Functionality

Sr.No.	Attribute or Method & Description
1	**axes** Returns a list of the row axis labels
2	**dtype** Returns the dtype of the object.
3	**empty** Returns True if series is empty.
4	**ndim** Returns the number of dimensions of the underlying data, by definition 1.

Series Basic Functionality

5	**size** Returns the number of elements in the underlying data.
6	**values** Returns the Series as ndarray.
7	**head()** Returns the first n rows.
8	**tail()** Returns the last n rows.

DataFrame Basic Functionality

Sr.No.	Attribute or Method & Description
1	**T** Transposes rows and columns.
2	**axes** Returns a list with the row axis labels and column axis labels as the only members.
3	**dtypes** Returns the dtypes in this object.
4	**empty** True if NDFrame is entirely empty [no items]; if any of the axes are of length 0.
5	**ndim** Number of axes / array dimensions.

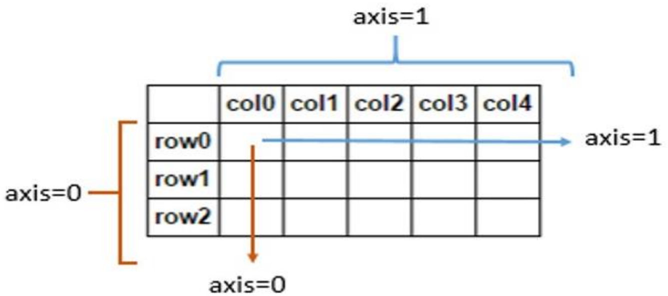
DataFrame Basic Functionality

6	**shape** Returns a tuple representing the dimensionality of the DataFrame.
7	**size** Number of elements in the NDFrame.
8	**values** Numpy representation of NDFrame.
9	**head()** Returns the first n rows.
10	**tail()** Returns last n rows.

Function Application

- To apply your own or another library's functions to Pandas objects, you should be aware of the three important methods. The appropriate method to use depends on whether your function expects to operate on an entire DataFrame, row- or column-wise, or element wise.
  - Table wise Function Application: pipe()
  - Row or Column Wise Function Application: apply()
  - Element wise Function Application: applymap()

Function Application




```
def adder(num1,num2):
    return num1+num2
```

```
   Age  Score  Salary
0  27.0   8.2  2500.0
1  22.0   9.0  1000.0
2  45.0   7.6   500.0
```

- Suppose df is data frame and adder is function
- df = df.pipe(adder,2)

```
   Age  Score  Salary
0  29.0  10.2  2502.0
1  24.0  11.0  1002.0
2  47.0   9.6   502.0
```

df = df['Salary'].map(lambda x:x*10)
#On Series data

```
0    25000.0
1    10000.0
2     5000.0
Name: Salary, dtype: float64
```

- df = df.apply(np.mean)

```
Age         31.333333
Score        8.266667
Salary    1333.333333
dtype: float64
```

df = df.applymap(lambda x:x*10)

```
    Age  Score   Salary
0  270.0  82.0  25000.0
1  220.0  90.0  10000.0
2  450.0  76.0   5000.0
```

- df = df.apply(np.mean, axis = 1)

```
0    845.066667
1    343.666667
2    184.200000
dtype: float64
```

df = df.apply(lambda x: x.max() - x.min())

```
Age         23.0
Score        1.4
Salary    2000.0
dtype: float64
```

Mapping

- map = {
  'label1' : 'value1,
  'label2' : 'value2,
  ...
  }

- The functions that you will see in this section perform specific operations, but they all accept a dict object.
  - replace()—Replaces values
  - map()—Creates a new column
  - rename()—Replaces the index values

Mapping

```
>>> frame = pd.DataFrame({ 'item':['ball','mug','pen','pencil','ashtray'],
...                        'color':['white','rosso','verde','black','yellow'],
                           'price':[5.56,4.20,1.30,0.56,2.75]})
>>> frame
    color     item    price
0   white     ball     5.56
1   rosso      mug     4.20
2   verde      pen     1.30
3   black   pencil     0.56
4  yellow  ashtray     2.75
```

```
>>> newcolors = {
...     'rosso': 'red',
...     'verde': 'green'
... }
```

Now the only thing you can do is use the `replace()` function with the mapping as an argument.

```
>>> frame.replace(newcolors)
    color     item  price
0   white     ball   5.56
1     red      mug   4.20
2   green      pen   1.30
3   black   pencil   0.56
4  yellow  ashtray   2.75
```

Adding Values via Mapping

```
>>> frame = pd.DataFrame({ 'item':['ball','mug','pen','pencil','ashtray'],
...                        'color':['white','red','green','black','yellow']})
>>> frame
    color     item
0   white     ball
1     red      mug
2   green      pen
3   black   pencil
4  yellow  ashtray
```

```
>>> prices = {
...     'ball' : 5.56,
...     'mug' : 4.20,
...     'bottle' : 1.30,
...     'scissors' : 3.41,
...     'pen' : 1.30,
...     'pencil' : 0.56,
...     'ashtray' : 2.75
... }
```

```
>>> frame['price'] = frame['item'].map(prices)
>>> frame
    color     item  price
0   white     ball   5.56
1     red      mug   4.20
2   green      pen   1.30
3   black   pencil   0.56
4  yellow  ashtray   2.75
```

Rename the Indexes of the Axes

```
>>> frame
    color     item  price
0   white     ball   5.56
1     red      mug   4.20
2   green      pen   1.30
3   black   pencil   0.56
4  yellow  ashtray   2.75
>>> reindex = {
...     0: 'first',
...     1: 'second',
...     2: 'third',
...     3: 'fourth',
...     4: 'fifth'}
>>> frame.rename(reindex)
          color     item  price
first     white     ball   5.56
second      red      mug   4.20
third     green      pen   1.30
fourth    black   pencil   0.56
fifth    yellow  ashtray   2.75
```

```
>>> recolumn = {
...     'item':'object',
...     'price': 'value'}
>>> frame.rename(index=reindex, columns=recolumn)
          color   object  value
first     white     ball   5.56
second      red      mug   4.20
third     green      pen   1.30
fourth    black   pencil   0.56
fifth    yellow  ashtray   2.75
```

Rename the Indexes of the Axes

```
>>> frame.rename(index={1:'first'}, columns={'item':'object'})
        color   object  price
0       white     ball   5.56
first     red      mug   4.20
2       green      pen   1.30
3       black   pencil   0.56
4      yellow  ashtray   2.75
```

So far you have seen that the `rename()` function returns a dataframe with the changes, leaving unchanged the original dataframe. If you want the changes to take effect on the object on which you call the function, you will set the `inplace` option to `True`.

```
>>> frame.rename(columns={'item':'object'}, inplace=True)
>>> frame
    color   object  price
0   white     ball   5.56
1     red      mug   4.20
2   green      pen   1.30
3   black   pencil   0.56
4  yellow  ashtray   2.75
```

Re-indexing

- Reindexing changes the row labels and column labels of a DataFrame. To reindex means to conform the data to match a given set of labels along a particular axis.
- Multiple operations can be accomplished through indexing like −
    - Reorder the existing data to match a new set of labels.
    - Insert missing value (NA) markers in label locations where no data for the label existed.

Example

```
import pandas as pd
import numpy as np

N=20

df = pd.DataFrame({
    'A': pd.date_range(start='2016-01-01',periods=N,freq='D'),
    'x': np.linspace(0,stop=N-1,num=N),
    'y': np.random.rand(N),
    'C': np.random.choice(['Low','Medium','High'],N).tolist(),
    'D': np.random.normal(100, 10, size=(N)).tolist()
})

print(df)

print(' ')
print('=============')
print(' ')

#reindex the DataFrame
df_reindexed = df.reindex(index=[0,2,5], columns=['A', 'C', 'B'])

print(df_reindexed)
```

```
             A       C           D     x         y
0   2016-01-01  Medium  102.633441   0.0  0.736833
1   2016-01-02    High  104.292073   1.0  0.362471
2   2016-01-03  Medium   99.963524   2.0  0.841574
3   2016-01-04     Low   93.014575   3.0  0.917657
4   2016-01-05  Medium  104.145754   4.0  0.825684
5   2016-01-06  Medium   82.369978   5.0  0.188074
6   2016-01-07  Medium  107.769696   6.0  0.786211
7   2016-01-08     Low  106.559870   7.0  0.811664
8   2016-01-09     Low   92.231004   8.0  0.333942
9   2016-01-10  Medium  104.774480   9.0  0.252270
10  2016-01-11     Low   87.682552  10.0  0.858438
11  2016-01-12     Low   97.608726  11.0  0.468110
12  2016-01-13     Low  107.884712  12.0  0.505663
13  2016-01-14     Low   98.667701  13.0  0.707653
14  2016-01-15  Medium   84.764679  14.0  0.843188
15  2016-01-16  Medium  106.471790  15.0  0.535894
16  2016-01-17    High   90.854407  16.0  0.539273
17  2016-01-18  Medium  105.756181  17.0  0.323379
18  2016-01-19     Low   84.810183  18.0  0.654856
19  2016-01-20  Medium  105.197082  19.0  0.063267

=============

           A       C    B
0 2016-01-01  Medium  NaN
2 2016-01-03  Medium  NaN
5 2016-01-06  Medium  NaN
```

Re-index to Align with Other Objects

```
import pandas as pd
import numpy as np

df1 = pd.DataFrame(np.random.randn(10,3),columns=['col1','col2','col3'])
df2 = pd.DataFrame(np.random.randn(7,3),columns=['col1','col2','col3'])

df1 = df1.reindex_like(df2)
print df1
```

	col1	col2	col3
0	-2.467652	-1.211687	-0.391761
1	-0.287396	0.522350	0.562512
2	-0.255409	-0.483250	1.866258
3	-1.150467	-0.646493	-0.222462
4	0.152768	-2.056643	1.877233
5	-1.155997	1.528719	-1.343719
6	-1.015606	-1.245936	-0.295275

Filling while ReIndexing

- reindex() takes an optional parameter method which is a filling method with values as follows −
    - pad/ffill − Fill values forward
    - bfill/backfill − Fill values backward
    - nearest − Fill from the nearest index values

Example

```python
import pandas as pd
import numpy as np

df1 = pd.DataFrame(np.random.randn(6,3),columns=['col1','col2','col3'])
df2 = pd.DataFrame(np.random.randn(2,3),columns=['col1','col2','col3'])


print(df1)
print(' ')
print(df2)

print(' ')

# Padding NAN's
print df2.reindex_like(df1)

print(' ')

# Now Fill the NAN's with preceding Values
print ("Data Frame with Forward Fill:")
print df2.reindex_like(df1,method='ffill')
```

```
       col1      col2      col3
0  0.477280 -0.440055 -1.239634
1  0.801811  0.388711 -0.345307
2 -0.745925 -0.287503  0.271269
3 -0.228431 -0.562865 -1.621816
4 -1.332601  1.451127 -0.459078
5  0.492429  0.695719 -0.322964

       col1      col2      col3
0 -0.891543 -0.364250  1.071647
1 -0.401467  0.191972  0.264598

       col1      col2      col3
0 -0.891543 -0.364250  1.071647
1 -0.401467  0.191972  0.264598
2       NaN       NaN       NaN
3       NaN       NaN       NaN
4       NaN       NaN       NaN
5       NaN       NaN       NaN

Data Frame with Forward Fill:
       col1      col2      col3
0 -0.891543 -0.364250  1.071647
1 -0.401467  0.191972  0.264598
2 -0.401467  0.191972  0.264598
3 -0.401467  0.191972  0.264598
4 -0.401467  0.191972  0.264598
5 -0.401467  0.191972  0.264598
```

Limits on Filling while Re-indexing

- The limit argument provides additional control over filling while reindexing. Limit specifies the maximum count of consecutive matches.

```
import pandas as pd
import numpy as np

df1 = pd.DataFrame(np.random.randn(6,3),columns=['col1','col2','col3'])
df2 = pd.DataFrame(np.random.randn(2,3),columns=['col1','col2','col3'])

# Padding NAN's
print df2.reindex_like(df1)

# Now Fill the NAN's with preceding Values
print ("Data Frame with Forward Fill limiting to 1:")
print df2.reindex_like(df1,method='ffill',limit=1)
```

```
       col1      col2      col3
0  0.247784  2.128727  0.702576
1 -0.055713 -0.021732 -0.174577
2       NaN       NaN       NaN
3       NaN       NaN       NaN
4       NaN       NaN       NaN
5       NaN       NaN       NaN

Data Frame with Forward Fill limiting to 1:
       col1      col2      col3
0  0.247784  2.128727  0.702576
1 -0.055713 -0.021732 -0.174577
2 -0.055713 -0.021732 -0.174577
3       NaN       NaN       NaN
4       NaN       NaN       NaN
5       NaN       NaN       NaN
```

Renaming

- The rename() method allows you to relabel an axis based on some mapping (a dict or Series) or an arbitrary function.

```
import pandas as pd
import numpy as np

df1 = pd.DataFrame(np.random.randn(6,3),columns=['col1','col2','col3'])
print df1

print ("After renaming the rows and columns:")
print df1.rename(columns={'col1' : 'c1', 'col2' : 'c2'},
index = {0 : 'apple', 1 : 'banana', 2 : 'durian'})
```

```
        col1      col2      col3
0   0.486791  0.105759  1.540122
1  -0.990237  1.007885 -0.217896
2  -0.483855 -1.645027 -1.194113
3  -0.122316  0.566277 -0.366028
4  -0.231524 -0.721172 -0.112007
5   0.438810  0.000225  0.435479

After renaming the rows and columns:
              c1        c2      col3
apple   0.486791  0.105759  1.540122
banana -0.990237  1.007885 -0.217896
durian -0.483855 -1.645027 -1.194113
3      -0.122316  0.566277 -0.366028
4      -0.231524 -0.721172 -0.112007
5       0.438810  0.000225  0.435479
```

ITERATION

- The behavior of basic iteration over Pandas objects depends on the type. When iterating over a Series, it is regarded as array-like, and basic iteration produces the values. Other data structures, like DataFrame and Panel, follow the **dict-like** convention of iterating over the **keys** of the objects.
- In short, basic iteration (for **i** in object) produces −
  - **Series** − values
  - **DataFrame** − column labels
  - **Panel** − item labels

ITERATOR COLUMN

- Iterating a DataFrame gives column names

```python
import pandas as pd
import numpy as np

N=20

df = pd.DataFrame({
    'A': pd.date_range(start='2016-01-01',periods=N,freq='D'),
    'x': np.linspace(0,stop=N-1,num=N),
    'y': np.random.rand(N),
    'C': np.random.choice(['Low','Medium','High'],N).tolist(),
    'D': np.random.normal(100, 10, size=(N)).tolist()
    })

for col in df:
   print(col)
```

```
A
C
D
x
y
```

ITERATOR ROWS

- To iterate over the rows of the DataFrame, we can use the following functions –
  - **iteritems()** – to iterate over the (key,value) pairs
  - **iterrows()** – iterate over the rows as (index,series) pairs
  - **itertuples()** – iterate over the rows as namedtuples

iteritems()

- Iterates over each column as key, value pair with label as key and column value as a Series object.

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns=['col1','col2','col3'])

print(df)

print(' ')

for key,value in df.iteritems():
   print(key,value)
```

```
       col1      col2      col3
0 -1.064935  2.037650 -1.091317
1 -1.820371  0.981087 -0.685399
2  0.109807 -0.648325  0.254567
3 -0.905518 -0.437735 -0.096516

('col1', 0   -1.064935
1   -1.820371
2    0.109807
3   -0.905518
Name: col1, dtype: float64)
('col2', 0    2.037650
1    0.981087
2   -0.648325
3   -0.437735
Name: col2, dtype: float64)
('col3', 0   -1.091317
1   -0.685399
2    0.254567
3   -0.096516
Name: col3, dtype: float64)
```

iterrows()

- iterrows() returns the iterator yielding each index value along with a series containing the data in each row.

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns = ['col1','col2','col3'])

print(df)

print(' ')

for row_index,row in df.iterrows():
   print(row_index,row)
```

```
       col1      col2      col3
0  3.186601  2.278300  0.980039
1  1.227548  0.895289 -0.524095
2  0.168116 -0.021478 -1.476323
3 -0.427900  0.009018  0.347493

(0, col1    3.186601
col2    2.278300
col3    0.980039
Name: 0, dtype: float64)
(1, col1    1.227548
col2    0.895289
col3   -0.524095
Name: 1, dtype: float64)
(2, col1    0.168116
col2   -0.021478
col3   -1.476323
Name: 2, dtype: float64)
(3, col1   -0.427900
col2    0.009018
col3    0.347493
Name: 3, dtype: float64)
```

itertuples()

- itertuples() method will return an iterator yielding a named tuple for each row in the DataFrame. The first element of the tuple will be the row's corresponding index value, while the remaining values are the row values.

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns = ['col1','col2','col3'])


print(df)

print(' ')

for row in df.itertuples():
    print(row)
```

```
       col1      col2      col3
0 -1.222998 -0.060763 -0.175401
1  0.609082  0.248033 -1.267356
2 -1.060177 -0.023235  0.875370
3  1.575262  0.770238 -0.049036

Pandas(Index=0, col1=-1.2229981344593324, col2=-0.060762990782568256, col3=-0.17540080460233923)
Pandas(Index=1, col1=0.60908214159083529, col2=0.24803265674889541, col3=-1.2673562738450024)
Pandas(Index=2, col1=-1.0601774305508465, col2=-0.023234683852895711, col3=0.8753702029249425)
Pandas(Index=3, col1=1.5752618196577792, col2=0.77023815349641189, col3=-0.049036106021165177)
```

Example

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns = ['col1','col2','col3'])

print(df)

print(' ')

for index, row in df.iterrows():
   row['a'] = 10
print(df)
```

```
       col1      col2      col3
0  0.558406  0.722226  1.270489
1  2.213536 -0.448291  0.617900
2 -0.758190 -0.293903  0.904212
3  1.461615  0.031728  0.417533

       col1      col2      col3
0  0.558406  0.722226  1.270489
1  2.213536 -0.448291  0.617900
2 -0.758190 -0.293903  0.904212
3  1.461615  0.031728  0.417533
```

Sorting

- There are two kinds of sorting available in Pandas. They are −
  - By label
  - By Actual Value
- Look at data generating randomly

```
import pandas as pd
import numpy as np

df=pd.DataFrame(np.random.randn(10,2),
index=[1,4,6,2,3,5,9,8,0,7],
columns=['col2','col1'])
```

	col2	col1
1	0.197920	-0.502069
4	1.610500	-1.253438
6	0.329770	-1.862410
2	0.798931	-0.823565
3	-0.412609	-1.244844
5	1.492556	-0.124418
9	-0.344938	-1.154500
8	1.694326	0.298172
0	0.000128	-1.884862
7	-1.541107	1.006505

Sorting Example

```
sorted_df_1=df.sort_index()

print(sorted_df_1)
```

```
       col2      col1
0  0.000128 -1.884862
1  0.197920 -0.502069
2  0.798931 -0.823565
3 -0.412609 -1.244844
4  1.610500 -1.253438
5  1.492556 -0.124418
6  0.329770 -1.862410
7 -1.541107  1.006505
8  1.694326  0.298172
9 -0.344938 -1.154500
```

```
sorted_df_2 = df.sort_index(ascending=False)

print(sorted_df_2)
```

```
       col2      col1
9 -0.344938 -1.154500
8  1.694326  0.298172
7 -1.541107  1.006505
6  0.329770 -1.862410
5  1.492556 -0.124418
4  1.610500 -1.253438
3 -0.412609 -1.244844
2  0.798931 -0.823565
1  0.197920 -0.502069
0  0.000128 -1.884862
```

Sorting Example

```
sorted_df_3=df.sort_index(axis=1)

print(sorted_df_3)
```

```
       col1      col2
1 -0.502069  0.197920
4 -1.253438  1.610500
6 -1.862410  0.329770
2 -0.823565  0.798931
3 -1.244844 -0.412609
5 -0.124418  1.492556
9 -1.154500 -0.344938
8  0.298172  1.694326
0 -1.884862  0.000128
7  1.006505 -1.541107
```

```
sorted_df_4 = df.sort_values(by='col1')

print(sorted_df_4)
```

```
       col2      col1
0  0.000128 -1.884862
6  0.329770 -1.862410
4  1.610500 -1.253438
3 -0.412609 -1.244844
9 -0.344938 -1.154500
2  0.798931 -0.823565
1  0.197920 -0.502069
5  1.492556 -0.124418
8  1.694326  0.298172
7 -1.541107  1.006505
```

Sorting Example

```python
sorted_df_5 = df.sort_values(by='col1' ,kind='mergesort')

print(sorted_df_5)
```

```
       col2      col1
0  0.000128 -1.884862
6  0.329770 -1.862410
4  1.610500 -1.253438
3 -0.412609 -1.244844
9 -0.344938 -1.154500
2  0.798931 -0.823565
1  0.197920 -0.502069
5  1.492556 -0.124418
8  1.694326  0.298172
7 -1.541107  1.006505
```

```python
sorted_df_6 = df.sort_values(by=['col1','col2'])

print(sorted_df_6)
```

```
       col2      col1
0  0.000128 -1.884862
6  0.329770 -1.862410
4  1.610500 -1.253438
3 -0.412609 -1.244844
9 -0.344938 -1.154500
2  0.798931 -0.823565
1  0.197920 -0.502069
5  1.492556 -0.124418
8  1.694326  0.298172
7 -1.541107  1.006505
```

Working with Text Data

- Pandas provides a set of string functions which make it easy to operate on string data. Most importantly, these functions ignore (or exclude) missing/NaN values.

Sr.No	Function & Description
1	**lower()** Converts strings in the Series/Index to lower case.
2	**upper()** Converts strings in the Series/Index to upper case.
3	**len()** Computes String length().
4	**strip()** Helps strip whitespace(including newline) from each string in the Series/index from both the sides.
5	**split(' ')** Splits each string with the given pattern.
6	**cat(sep=' ')** Concatenates the series/index elements with given separator.
7	**get_dummies()** Returns the DataFrame with One-Hot Encoded values.

Working with Text Data

8	**contains(pattern)** Returns a Boolean value True for each element if the substring contains in the element, else False.
9	**replace(a,b)** Replaces the value **a** with the value **b**.
10	**repeat(value)** Repeats each element with specified number of times.
11	**count(pattern)** Returns count of appearance of pattern in each element.
12	**startswith(pattern)** Returns true if the element in the Series/Index starts with the pattern.
13	**endswith(pattern)** Returns true if the element in the Series/Index ends with the pattern.
14	**find(pattern)** Returns the first position of the first occurrence of the pattern.

Working with Text Data

15	**findall(pattern)** Returns a list of all occurrence of the pattern.
16	**swapcase** Swaps the case lower/upper.
17	**islower()** Checks whether all characters in each string in the Series/Index in lower case or not. Returns Boolean
18	**isupper()** Checks whether all characters in each string in the Series/Index in upper case or not. Returns Boolean.
19	**isnumeric()** Checks whether all characters in each string in the Series/Index are numeric. Returns Boolean.

Options and Customization

- get_option(param): get_option takes a single parameter and returns the value as given in the table
- set_option(param,value): set_option takes two arguments and sets the value to the parameter as shown table
- reset_option(param): takes an argument and sets the value back to the default value.
- describe_option(param): describe_option prints the description of the argument.
- option_context(): option_context context manager is used to set the option in with statement temporarily. Option values are restored automatically when you exit the with block

Sr.No	Parameter & Description
1	**display.max_rows** Displays maximum number of rows to display
2	**2 display.max_columns** Displays maximum number of columns to display
3	**display.expand_frame_repr** Displays DataFrames to Stretch Pages
4	**display.max_colwidth** Displays maximum column width
5	**display.precision** Displays precision for decimal numbers

Indexing and Selecting Data in Pandas

Indexing and Selecting Data

- The Python and NumPy indexing operators "[ ]" and attribute operator "." provide quick and easy access to Pandas data structures across a wide range of use cases. However, since the type of the data to be accessed isn't known in advance, directly using standard operators has some optimization limits. For production code, we recommend that you take advantage of the optimized pandas data access methods explained.
- Pandas now supports three types of Multi-axes indexing; the three types are mentioned in the following table.

Sr.No	Indexing & Description
1	**.loc()** Label based
2	**.iloc()** Integer based
3	**.ix()** Both Label and Integer based

.loc()

- Pandas provide various methods to have purely label based indexing. When slicing, the start bound is also included. Integers are valid labels, but they refer to the label and not the position.
- **.loc()** has multiple access methods like:
  - A single scalar label
  - A list of labels
  - A slice object
  - A Boolean array
- **loc** takes two single/list/range operator separated by ','. The first one indicates the row and the second one indicates columns.

.loc() Example

```
#import the pandas library and aliasing as pd
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(8, 4),
index = ['a','b','c','d','e','f','g','h'],
columns = ['A', 'B', 'C', 'D'])
```

	A	B	C	D
a	1.695355	0.462850	-0.644750	1.339618
b	-0.224149	-0.830238	-0.183428	1.272660
c	-1.691320	-0.729269	-1.635839	-0.395096
d	0.308963	-0.977447	-0.446715	-1.427920
e	-0.912702	0.628778	1.460212	0.588769
f	0.732504	-0.214279	0.498870	-1.508137
g	1.301601	-1.564609	-0.058068	-0.612667
h	0.729417	2.626195	0.401886	0.290472

.loc() Example

```
#select all rows for a specific column
print(df.loc[:,'A'])
```

	A	B	C	D
a	1.695355	0.462850	-0.644750	1.339618
b	-0.224149	-0.830238	-0.183428	1.272660
c	-1.691320	-0.729269	-1.635839	-0.395096
d	0.308963	-0.977447	-0.446715	-1.427920
e	-0.912702	0.628778	1.460212	0.588769
f	0.732504	-0.214279	0.498870	-1.508137
g	1.301601	-1.564609	-0.058068	-0.612667
h	0.729417	2.626195	0.401886	0.290472

```
a    1.695355
b   -0.224149
c   -1.691320
d    0.308963
e   -0.912702
f    0.732504
g    1.301601
h    0.729417
Name: A, dtype: float64
```

.loc() Example

```python
# Select all rows for multiple columns, say list[]
print(df.loc[:,['A','C']])
```

```
          A         B         C         D
a  1.695355  0.462850 -0.644750  1.339618
b -0.224149 -0.830238 -0.183428  1.272660
c -1.691320 -0.729269 -1.635839 -0.395096
d  0.308963 -0.977447 -0.446715 -1.427920
e -0.912702  0.628778  1.460212  0.588769
f  0.732504 -0.214279  0.498870 -1.508137
g  1.301601 -1.564609 -0.058068 -0.612667
h  0.729417  2.626195  0.401886  0.290472
```

```
          A         C
a  1.695355 -0.644750
b -0.224149 -0.183428
c -1.691320 -1.635839
d  0.308963 -0.446715
e -0.912702  1.460212
f  0.732504  0.498870
g  1.301601 -0.058068
h  0.729417  0.401886
```

.loc() Example

```
# Select few rows for multiple columns, say list[]
print(df.loc[['a','b','f','h'],['A','C']])
```

	A	B	C	D
a	1.695355	0.462850	-0.644750	1.339618
b	-0.224149	-0.830238	-0.183428	1.272660
c	-1.691320	-0.729269	-1.635839	-0.395096
d	0.308963	-0.977447	-0.446715	-1.427920
e	-0.912702	0.628778	1.460212	0.588769
f	0.732504	-0.214279	0.498870	-1.508137
g	1.301601	-1.564609	-0.058068	-0.612667
h	0.729417	2.626195	0.401886	0.290472

	A	C
a	1.695355	-0.644750
b	-0.224149	-0.183428
f	0.732504	0.498870
h	0.729417	0.401886

.loc() Example

```
# Select range of rows for all columns
print(df.loc['a':'h'])
```

```
          A         B         C         D
a  1.695355  0.462850 -0.644750  1.339618
b -0.224149 -0.830238 -0.183428  1.272660
c -1.691320 -0.729269 -1.635839 -0.395096
d  0.308963 -0.977447 -0.446715 -1.427920
e -0.912702  0.628778  1.460212  0.588769
f  0.732504 -0.214279  0.498870 -1.508137
g  1.301601 -1.564609 -0.058068 -0.612667
h  0.729417  2.626195  0.401886  0.290472
```

```
          A         B         C         D
a  1.695355  0.462850 -0.644750  1.339618
b -0.224149 -0.830238 -0.183428  1.272660
c -1.691320 -0.729269 -1.635839 -0.395096
d  0.308963 -0.977447 -0.446715 -1.427920
e -0.912702  0.628778  1.460212  0.588769
f  0.732504 -0.214279  0.498870 -1.508137
g  1.301601 -1.564609 -0.058068 -0.612667
h  0.729417  2.626195  0.401886  0.290472
```

.loc() Example

```
# for getting values with a boolean array
print(df.loc['a']>0)
```

```
          A         B         C         D
a  1.695355  0.462850 -0.644750  1.339618
b -0.224149 -0.830238 -0.183428  1.272660
c -1.691320 -0.729269 -1.635839 -0.395096
d  0.308963 -0.977447 -0.446715 -1.427920
e -0.912702  0.628778  1.460212  0.588769
f  0.732504 -0.214279  0.498870 -1.508137
g  1.301601 -1.564609 -0.058068 -0.612667
h  0.729417  2.626195  0.401886  0.290472
```

```
A     True
B     True
C    False
D     True
Name: a, dtype: bool
```

.iloc()

- Pandas provide various methods in order to get purely integer based indexing. Like python and numpy, these are **0-based** indexing.
- The various access methods are as follows:
  - An Integer
  - A list of integers
  - A range of values

.iloc() Example

```python
# import the pandas library and aliasing as pd
import pandas as pd
import numpy as np

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

#print
print(df)
```

```
          A         B         C         D
0  0.176753 -0.775588  0.776157 -0.557363
1  1.201638 -1.326106 -1.184976 -0.766993
2  0.411747  1.221240  0.531377 -1.802342
3  0.038384  0.455340 -0.183154  1.001551
4  1.411158  0.245044  0.550815 -0.373446
5  0.638930 -1.200300 -0.429424 -0.533487
6 -0.318424 -0.888178 -0.179147 -0.519741
7 -0.855873 -0.574493 -0.657266 -1.156689
```

.iloc() Example

```
# select all rows for a specific column
print(df.iloc[:4])
```

	A	B	C	D
0	0.176753	-0.775588	0.776157	-0.557363
1	1.201638	-1.326106	-1.184976	-0.766993
2	0.411747	1.221240	0.531377	-1.802342
3	0.038384	0.455340	-0.183154	1.001551
4	1.411158	0.245044	0.550815	-0.373446
5	0.638930	-1.200300	-0.429424	-0.533487
6	-0.318424	-0.888178	-0.179147	-0.519741
7	-0.855873	-0.574493	-0.657266	-1.156689

	A	B	C	D
0	0.176753	-0.775588	0.776157	-0.557363
1	1.201638	-1.326106	-1.184976	-0.766993
2	0.411747	1.221240	0.531377	-1.802342
3	0.038384	0.455340	-0.183154	1.001551

.iloc() Example

```python
# Integer slicing
print(df.iloc[:4])
print(df.iloc[1:5, 2:4])
```

	A	B	C	D
0	0.176753	-0.775588	0.776157	-0.557363
1	1.201638	-1.326106	-1.184976	-0.766993
2	0.411747	1.221240	0.531377	-1.802342
3	0.038384	0.455340	-0.183154	1.001551

	C	D
1	-1.184976	-0.766993
2	0.531377	-1.802342
3	-0.183154	1.001551
4	0.550815	-0.373446

	A	B	C	D
0	0.176753	-0.775588	0.776157	-0.557363
1	1.201638	-1.326106	-1.184976	-0.766993
2	0.411747	1.221240	0.531377	-1.802342
3	0.038384	0.455340	-0.183154	1.001551
4	1.411158	0.245044	0.550815	-0.373446
5	0.638930	-1.200300	-0.429424	-0.533487
6	-0.318424	-0.888178	-0.179147	-0.519741
7	-0.855873	-0.574493	-0.657266	-1.156689

.iloc() Example

```python
# Slicing through list of values
print(df.iloc[[1, 3, 5], [1, 3]])
print(df.iloc[1:3, :])
print(df.iloc[:,1:3])
```

```
          B         D
1 -1.326106 -0.766993
3  0.455340  1.001551
5 -1.200300 -0.533487
```

```
          A         B         C         D
1  1.201638 -1.326106 -1.184976 -0.766993
2  0.411747  1.221240  0.531377 -1.802342
```

```
          B         C
0 -0.775588  0.776157
1 -1.326106 -1.184976
2  1.221240  0.531377
3  0.455340 -0.183154
4  0.245044  0.550815
5 -1.200300 -0.429424
6 -0.888178 -0.179147
7 -0.574493 -0.657266
```

```
          A         B         C         D
0  0.176753 -0.775588  0.776157 -0.557363
1  1.201638 -1.326106 -1.184976 -0.766993
2  0.411747  1.221240  0.531377 -1.802342
3  0.038384  0.455340 -0.183154  1.001551
4  1.411158  0.245044  0.550815 -0.373446
5  0.638930 -1.200300 -0.429424 -0.533487
6 -0.318424 -0.888178 -0.179147 -0.519741
7 -0.855873 -0.574493 -0.657266 -1.156689
```

.ix()

- Besides pure label based and integer based, Pandas provides a hybrid method for selections and subsetting the object using the .ix() operator.

```
import pandas as pd
import numpy as np

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

#df
print(df)
```

```
          A         B         C         D
0  0.378898  0.133670  0.136070  0.127399
1 -0.499039  2.357291 -1.150006  0.935712
2 -2.329760 -0.380842  0.063687  1.551128
3 -1.400219  0.317153  0.651748 -1.084645
4 -0.252273 -0.652334 -1.204376  1.341390
5  0.623551 -0.820163  0.610148  0.894935
6 -1.855714 -0.442705  0.665694  0.374564
7 -1.282746 -0.646424 -0.021149  0.006043
```

.ix() Example

```python
# Integer slicing
print(df.ix[:4])
```

```
          A         B         C         D
0  0.378898  0.133670  0.136070  0.127399
1 -0.499039  2.357291 -1.150006  0.935712
2 -2.329760 -0.380842  0.063687  1.551128
3 -1.400219  0.317153  0.651748 -1.084645
4 -0.252273 -0.652334 -1.204376  1.341390
```

```python
# Index slicing
print(df.ix[:,'A'])
```

```
0    0.378898
1   -0.499039
2   -2.329760
3   -1.400219
4   -0.252273
5    0.623551
6   -1.855714
7   -1.282746
Name: A, dtype: float64
```

```
          A         B         C         D
0  0.378898  0.133670  0.136070  0.127399
1 -0.499039  2.357291 -1.150006  0.935712
2 -2.329760 -0.380842  0.063687  1.551128
3 -1.400219  0.317153  0.651748 -1.084645
4 -0.252273 -0.652334 -1.204376  1.341390
5  0.623551 -0.820163  0.610148  0.894935
6 -1.855714 -0.442705  0.665694  0.374564
7 -1.282746 -0.646424 -0.021149  0.006043
```

Use of Notations

- Getting values from the Pandas object with Multi-axes indexing uses the following notation
- **Note**: .iloc() & .ix() applies the same indexing options and Return value.

Object	Indexers	Return Type
Series	s.loc[indexer]	Scalar value
DataFrame	df.loc[row_index,col_index]	Series object
Panel	p.loc[item_index,major_index, minor_index]	p.loc[item_index,major_index, minor_index]

(Example 1) Use the basic indexing operator '[ ]'

```
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(8, 4), columns = ['A', 'B', 'C', 'D'])

print(df)
```

```
          A         B         C         D
0  0.170981 -1.474156  0.544007 -1.918815
1 -0.183828  0.322550  0.443701 -0.531228
2  0.114509 -0.473415 -1.736726 -1.137762
3 -0.630348 -0.268956  0.981704  1.121474
4 -0.121557 -1.798246  0.551525 -0.072194
5  0.345434 -1.330808  1.411509  1.100317
6  0.117264  1.135388 -1.672977 -0.126768
7 -0.622439  0.918388  0.936736  0.945120
```

(Example 1) Use the basic indexing operator '[ ]'

```
print(df['A'])
```

```
0    0.170981
1   -0.183828
2    0.114509
3   -0.630348
4   -0.121557
5    0.345434
6    0.117264
7   -0.622439
Name: A, dtype: float64
```

```
print(df[['A','B']])
```

```
          A         B
0  0.170981 -1.474156
1 -0.183828  0.322550
2  0.114509 -0.473415
3 -0.630348 -0.268956
4 -0.121557 -1.798246
5  0.345434 -1.330808
6  0.117264  1.135388
7 -0.622439  0.918388
Empty DataFrame
Columns: [A, B, C, D]
Index: []
```

```
print(df[2:2])
```

```
Empty DataFrame
Columns: [A, B, C, D]
Index: []
```

```
          A         B         C         D
0  0.170981 -1.474156  0.544007 -1.918815
1 -0.183828  0.322550  0.443701 -0.531228
2  0.114509 -0.473415 -1.736726 -1.137762
3 -0.630348 -0.268956  0.981704  1.121474
4 -0.121557 -1.798246  0.551525 -0.072194
5  0.345434 -1.330808  1.411509  1.100317
6  0.117264  1.135388 -1.672977 -0.126768
7 -0.622439  0.918388  0.936736  0.945120
```

Sort, Filter, Aggregation, Grouping, Pivot, Concatenation, Merge/Join in Pandas

Sort

- *Sort theo 1 column, mặc định là tăng dần*: **df.sort_values(by='TOTAL')**

	ID	USER_ID	PRODUCT_ID	SUBTOTAL	TAX	TOTAL	DISCOUNT	CREATED_AT	QUANTITY
92	93	17	15	25.098764	0.00	25.175195	NaN	2017-06-18T11:15:50.035	4
75	76	15	185	26.384667	1.72	28.098903	NaN	2016-12-19T19:40:17.782	2
5	6	1	60	29.802148	1.64	31.441679	NaN	2019-11-06T16:38:50.134	3
70	71	12	161	31.727470	1.27	32.940866	NaN	2017-09-01T11:51:46.788	4
69	70	12	22	32.136780	1.29	33.418084	NaN	2019-11-21T11:21:36.739	3

- Sort theo thứ tự giảm dần: df.sort_values(by='TOTAL', ascending=False)
- Sort theo nhiều trường: df.sort_values(by=['QUANTITY','TOTAL'])
- Sort nhiều trường theo thứ tự khác nhau: df.sort_values(by=['QUANTITY','TOTAL'], ascending=[True, False])

Filter (lọc dữ liệu)

- Filter lấy ra các cột của dataframe: df.filter(items=['USER_ID', 'TAX'])
- Filter lấy ra các cột theo regular expression: df.filter(regex='T$', axis=1)

	DISCOUNT	CREATED_AT
0	NaN	2019-02-11T21:40:27.892
1	NaN	2018-05-15T08:04:04.58
2	6.416679	2019-12-06T22:22:48.544
3	NaN	2019-08-22T16:30:42.392
4	NaN	2018-10-10T03:34:47.309
...	...	...

Filter

- Filter các row chứa ký tự: df.filter(like='bbi', axis=0)
- Filter các row theo biểu thức so sánh
    - Ví dụ lấy tất cả các order có TOTAL lớn hơn 100: df[df['TOTAL'] > 100]

- Filter theo một hàm tự định nghĩa

```
def custom(tax, total):
        return ( total - tax > 100)

df[custom(df['TAX'], df['TOTAL'])]
```

Aggregation

```python
# importing pandas package
import pandas as pd

# making data frame from csv file
df = pd.read_csv("nba.csv")

# printing the first 10 rows of the dataframe
print(df[:10])
```

Name	Team	Number	Position	Age	Height	Weight	College	Salary
Avery Bradley	Boston Celtics	0	PG	25	180	77.2	Texas	7730337
Jae Crowder	Boston Celtics	99	SF	25	172	65	Georgia State	6796117
John Holland	Boston Celtics	30	SG	27	165	55	Boston University	
R.J. Hunter	Boston Celtics	28	SG	22	177	85	Georgia State	1148640
Jonas Jerebko	Boston Celtics	8	PF	29	198	100		5000000
Bojan Bogdanovic	Brooklyn Nets	44	SG	27	150	52		3425510
Markel Brown	Brooklyn Nets	22	SG	24	188	90	Oklahoma State	845059
Arron Afflalo	New York Knicks	4	SG	30	175	70	UCLA	8000000
Lou Amundson	New York Knicks	17	PF	33	171	72	UCLA	1635476
Elton Brand	Philadelphia 76ers	42	PF	37	158	60	UCLA	
Isaiah Canaan	Philadelphia 76ers	0	PG	25	179	70	UCLA	947276
Robert Covington	Philadelphia 76ers	33	SF	25	180	78	Georgia State	1000000
Joel Embiid	Philadelphia 76ers	21	C	22	179	76	Texas	4626960
Bismack Biyombo	Toronto Raptors	8	C	23	169	68.5		2814000
Bruno Caboclo	Toronto Raptors	20	SF	20	170	73.5		1524000

Example

```python
# Applying aggregation across all the columns
# sum and min will be found for each
print(df.aggregate(['sum', 'min']))
```

```python
print(df.aggregate([np.sum,np.min]))
```

```
                                           Name  ...      Salary
sum  Avery BradleyJae CrowderJohn HollandR.J. Hunte...  ...  45493375.0
min                                Arron Afflalo  ...    845059.0
```

Example

```
# We are going to find aggregation for these columns
newAggre = df.aggregate({"Number":['sum', 'min'],
                "Age":['max', 'min'],
                "Weight":['min', 'sum'],
                "Salary":['sum']})

print(newAggre)
```

```
     Number   Age  Weight      Salary
max     NaN  37.0     NaN         NaN
min     0.0  20.0    52.0         NaN
sum   376.0   NaN  1092.2  45493375.0
```

Example

```python
#Apply Different Functions to Different Columns of a Dataframe
print(df.aggregate({'Age' : np.sum,'Salary' : np.mean}))
```

```
Age          3.940000e+02
Salary       3.499490e+06
dtype: float64
```

Example

```
print(df[['Number','Age','Weight','Salary']].aggregate(np.sum))
```

```
Number           376.0
Age              394.0
Weight          1092.2
Salary      45493375.0
dtype: float64
```

Group

```
print(df.groupby('Team'))
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x000001F036F69F98>
```

Group

```python
print(df.groupby('Team').groups)
```

```
{'Boston Celtics': Int64Index([0, 1, 2, 3, 4], dtype='int64'), 'Brooklyn Nets': Int64Index([5, 6], dtype='int64'), 'New York Knicks': Int64Index([7, 8], dtype='int64'), 'Philadelphia 76ers': Int64Index([9, 10, 11, 12], dtype='int64'), 'Toronto Raptors': Int64Index([13, 14], dtype='int64')}
```

Group

```
print(df.groupby('Team')['Age'].agg(['count']))
```

```
                    count
Team
Boston Celtics          5
Brooklyn Nets           2
New York Knicks         2
Philadelphia 76ers      4
Toronto Raptors         2
```

Group

```
print(df.groupby('Team')['Age'].agg(['count','min','max','mean']))
```

```
                     count   min   max   mean
Team
Boston Celtics           5  22.0  29.0  25.60
Brooklyn Nets            2  24.0  27.0  25.50
New York Knicks          2  30.0  33.0  31.50
Philadelphia 76ers       4  22.0  37.0  27.25
Toronto Raptors          2  20.0  23.0  21.50
```

Group

```
print(df.groupby('Team')['Age','Weight'].agg(['count','min','max','mean']))
```

	Age				Weight			
	count	min	max	mean	count	min	max	mean
Team								
Boston Celtics	5	22.0	29.0	25.60	5	55.0	100.0	76.44
Brooklyn Nets	2	24.0	27.0	25.50	2	52.0	90.0	71.00
New York Knicks	2	30.0	33.0	31.50	2	70.0	72.0	71.00
Philadelphia 76ers	4	22.0	37.0	27.25	4	60.0	78.0	71.00
Toronto Raptors	2	20.0	23.0	21.50	2	68.5	73.5	71.00

Group

```
print(df.groupby(['Team','College'])['Age','Weight'].agg(['count','min','max','mean']))
```

```
                                        Age              ... Weight
                                      count   min   max ...    min   max  mean
Team               College                               ...
Boston Celtics     Boston University      1  27.0  27.0 ...   55.0  55.0  55.0
                   Georgia State          2  22.0  25.0 ...   65.0  85.0  75.0
                   Texas                  1  25.0  25.0 ...   77.2  77.2  77.2
Brooklyn Nets      Oklahoma State         1  24.0  24.0 ...   90.0  90.0  90.0
New York Knicks    UCLA                   2  30.0  33.0 ...   70.0  72.0  71.0
Philadelphia 76ers Georgia State          1  25.0  25.0 ...   78.0  78.0  78.0
                   Texas                  1  22.0  22.0 ...   76.0  76.0  76.0
                   UCLA                   2  25.0  37.0 ...   60.0  70.0  65.0
```

Grouping with user-define function

- Chẳng hạn group lại theo Team và lấy ra tổng số tuổi của 10 bản ghi đầu tiên

```
def custom_aggregate(series):
        return series.head(10).sum()

df.groupby([‘Team’])[‘Age’].agg(custom_aggregate)
```

Pivot

- One of the most common tasks in data science is to manipulate the data frame we have to a specific format.
- Give data about life expectancy (expectancy refers to the number of years a person is expected to live based on the statistical average. Life expectancy varies by geographical area and by era.)
- Python Pandas function pivot_table help us with the summarization and conversion of dataframe in long form to dataframe in wide form, in a variety of complex scenarios.

continent	year	lifeExp
Europe	1972	69.210
Asia	1992	75.190
Asia	1987	53.914
Americas	1962	70.210
Europe	1967	69.610

Raw data: df

continent	Africa	Americas	Asia	Europe	Oceania
year					
1952	30.000	37.579	28.801	43.585	69.12
1957	31.570	40.696	30.332	48.079	70.26
1962	32.767	43.428	31.997	52.098	70.93
1967	34.113	45.032	34.020	54.336	71.10
1972	35.400	46.714	36.088	57.005	71.89

Pivot

Pandas Simple Pivot

- A simple example of Python Pivot using a dataframe with jus two columns. Let us subset our dataframe to contain just two columns, continent and lifeExp

continent	lifeExp
Africa	72.301
Africa	57.678
Europe	68.000
Europe	64.030
Asia	37.373

→

continent	Africa	Americas	Asia	Europe
lifeExp	48.86533	64.658737	60.064903	71.903686

```
pd.pivot_table(df[['continent','lifeExp']], values='lifeExp', columns='continent')
```

Pandas pivot_table on a data frame with three columns

- Pandas pivot_table gets more useful when we try to summarize and convert a tall data frame with more than two variables into a wide data frame. Use three columns; continent, year, and lifeExp

pd.pivot_table(df[['continent', 'year','lifeExp']], values='lifeExp', index=['year'], columns='continent')

	continent	year	lifeExp
0	Asia	1952	28.801
1	Asia	1957	30.332
2	Asia	1962	31.997
3	Asia	1967	34.020
4	Asia	1972	36.088
...	...	...	...
1699	Africa	1987	62.351
1700	Africa	1992	60.377
1701	Africa	1997	46.809
1702	Africa	2002	39.989
1703	Africa	2007	43.487

continent	Africa	Americas	Asia	Europe	Oceania
year					
1952	39.135500	53.27984	46.314394	64.408500	69.2550
1957	41.266346	55.96028	49.318544	66.703067	70.2950
1962	43.319442	58.39876	51.563223	68.539233	71.0850
1967	45.334538	60.41092	54.663640	69.737600	71.3100
1972	47.450942	62.39492	57.319269	70.775033	71.9100
1977	49.580423	64.39156	59.610556	71.937767	72.8550
1982	51.592865	66.22884	62.617939	72.806400	74.2900
1987	53.344788	68.09072	64.851182	73.642167	75.3200
1992	53.629577	69.56836	66.537212	74.440100	76.9450
1997	53.598269	71.15048	68.020515	75.505167	78.1900
2002	53.325231	72.42204	69.233879	76.700600	79.7400
2007	54.806038	73.60812	70.728485	77.648600	80.7195

Pandas pivot_table with Different Aggregating Function

- Pivot_table uses mean function for aggregating or summarizing data by default. We can change the aggregating function, if needed.
- For example, we can use aggfunc='max' to compute "maximum" lifeExp instead of "mean" lifeExp for each year and continent values.

pd.pivot_table(df[['continent', 'year','lifeExp']], values='lifeExp', index=['year'], columns='continent',aggfunc='max')

	continent	year	lifeExp
0	Asia	1952	28.801
1	Asia	1957	30.332
2	Asia	1962	31.997
3	Asia	1967	34.020
4	Asia	1972	36.088
...	...	...	...
1699	Africa	1987	62.351
1700	Africa	1992	60.377
1701	Africa	1997	46.809
1702	Africa	2002	39.989
1703	Africa	2007	43.487

continent	Africa	Americas	Asia	Europe	Oceania
year					
1952	52.724	68.750	65.390	72.670	69.390
1957	58.089	69.960	67.840	73.470	70.330
1962	60.246	71.300	69.390	73.680	71.240
1967	61.557	72.130	71.430	74.160	71.520
1972	64.274	72.880	73.420	74.720	71.930
1977	67.064	74.210	75.380	76.110	73.490
1982	69.885	75.760	77.110	76.990	74.740
1987	71.913	76.860	78.670	77.410	76.320
1992	73.615	77.950	79.360	78.770	77.560
1997	74.772	78.610	80.690	79.390	78.830
2002	75.744	79.770	82.000	80.620	80.370
2007	76.442	80.653	82.603	81.757	81.235

Pandas pivot_table with Different Aggregating Function

- pd.pivot_table(df[['continent', 'year','lifeExp']], values='lifeExp', index=['year'], columns='continent',aggfunc=[min,max])

	continent	year	lifeExp
0	Asia	1952	28.801
1	Asia	1957	30.332
2	Asia	1962	31.997
3	Asia	1967	34.020
4	Asia	1972	36.088
...	...	...	...
1699	Africa	1987	62.351
1700	Africa	1992	60.377
1701	Africa	1997	46.809
1702	Africa	2002	39.989
1703	Africa	2007	43.487

	min				...	max			
continent	Africa	Americas	Asia	Europe	...	Americas	Asia	Europe	Oceania
year					...				
1952	30.000	37.579	28.801	43.585	...	68.750	65.390	72.670	69.390
1957	31.570	40.696	30.332	48.079	...	69.960	67.840	73.470	70.330
1962	32.767	43.428	31.997	52.098	...	71.300	69.390	73.680	71.240
1967	34.113	45.032	34.020	54.336	...	72.130	71.430	74.160	71.520
1972	35.400	46.714	36.088	57.005	...	72.880	73.420	74.720	71.930
1977	36.788	49.923	31.220	59.507	...	74.210	75.380	76.110	73.490
1982	38.445	51.461	39.854	61.036	...	75.760	77.110	76.990	74.740
1987	39.906	53.636	40.822	63.108	...	76.860	78.670	77.410	76.320
1992	23.599	55.089	41.674	66.146	...	77.950	79.360	78.770	77.560
1997	36.087	56.671	41.763	68.835	...	78.610	80.690	79.390	78.830
2002	39.193	58.137	42.129	70.845	...	79.770	82.000	80.620	80.370
2007	39.613	60.916	43.828	71.777	...	80.653	82.603	81.757	81.235

Melt

- Pandas melt() function is used to change the DataFrame format from wide to long. It's used to create a specific format of the DataFrame object where one or more columns work as identifiers. All the remaining columns are treated as values and unpivoted to the row axis and only two columns – variable and value.

```
import pandas as pd

d1 = {"Name": ["Pankaj", "Lisa", "David"], "ID": [1, 2, 3], "Role": ["CEO", "Editor", "Author"]}

df = pd.DataFrame(d1)

print(df)

df_melted = pd.melt(df, id_vars=["ID"], value_vars=["Name", "Role"])

print(df_melted)
```

```
     Name  ID    Role
0  Pankaj   1     CEO
1    Lisa   2  Editor
2   David   3  Author
```

```
   ID variable   value
0   1     Name  Pankaj
1   2     Name    Lisa
2   3     Name   David
3   1     Role     CEO
4   2     Role  Editor
5   3     Role  Author
```

Concatenation

```python
df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                    'B': ['B0', 'B1', 'B2', 'B3'],
                    'C': ['C0', 'C1', 'C2', 'C3'],
                    'D': ['D0', 'D1', 'D2', 'D3']},
                   index=[0, 1, 2, 3])


df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
                    'B': ['B4', 'B5', 'B6', 'B7'],
                    'C': ['C4', 'C5', 'C6', 'C7'],
                    'D': ['D4', 'D5', 'D6', 'D7']},
                   index=[4, 5, 6, 7])


df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
                    'B': ['B8', 'B9', 'B10', 'B11'],
                    'C': ['C8', 'C9', 'C10', 'C11'],
                    'D': ['D8', 'D9', 'D10', 'D11']},
                   index=[8, 9, 10, 11])


frames = [df1, df2, df3]

result = pd.concat(frames)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

df3

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Result

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Advanced Concatenation

```python
df4 = pd.DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
                    'D': ['D2', 'D3', 'D6', 'D7'],
                    'F': ['F2', 'F3', 'F6', 'F7']},
                   index=[2, 3, 6, 7])


result = pd.concat([df1, df4], axis=1, sort=False)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3
6	NaN	NaN	NaN	NaN	B6	D6	F6
7	NaN	NaN	NaN	NaN	B7	D7	F7

```python
result = pd.concat([df1, df4], axis=1, join='inner')
```

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

Advanced Concatenation

```
pd.concat([df1, df4.reindex(df1.index)], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

https://pandas.pydata.org/pandas-docs/stable/user_guide/merging.html

Merging

```
left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
                     'key2': ['K0', 'K1', 'K0', 'K1'],
                     'A': ['A0', 'A1', 'A2', 'A3'],
                     'B': ['B0', 'B1', 'B2', 'B3']})


right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
                      'key2': ['K0', 'K0', 'K0', 'K0'],
                      'C': ['C0', 'C1', 'C2', 'C3'],
                      'D': ['D0', 'D1', 'D2', 'D3']})


result = pd.merge(left, right, on=['key1', 'key2'])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

Joining

```
left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                     'B': ['B0', 'B1', 'B2']},
                    index=['K0', 'K1', 'K2'])


right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
                      'D': ['D0', 'D2', 'D3']},
                     index=['K0', 'K2', 'K3'])


result = left.join(right)
```

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K1	A1	B1	NaN	NaN
K2	A2	B2	C2	D2

Data Manipulation in Pandas

Regex

```
import re

pattern = '^a...s$'
test_string = 'abyss'
result = re.match(pattern, test_string)

if result:
  print("Search successful.")
else:
  print("Search unsuccessful.")
```

A Regular Expression (RegEx) is a sequence of characters that defines a search pattern.

```
import re

string = '39801 356, 2102 1111'

# Three digit number followed by space followed by two digit number
pattern = '(\d{3}) (\d{2})'

# match variable contains a Match object.
match = re.search(pattern, string)

if match:
  print(match.group())
else:
  print("pattern not found")
```

Date Functionality

```
import pandas as pd

df = pd.date_range('1/1/2020', periods=25)

print(df)
```

```
DatetimeIndex(['2020-01-01', '2020-01-02', '2020-01-03', '2020-01-04',
               '2020-01-05', '2020-01-06', '2020-01-07', '2020-01-08',
               '2020-01-09', '2020-01-10', '2020-01-11', '2020-01-12',
               '2020-01-13', '2020-01-14', '2020-01-15', '2020-01-16',
               '2020-01-17', '2020-01-18', '2020-01-19', '2020-01-20',
               '2020-01-21', '2020-01-22', '2020-01-23', '2020-01-24',
               '2020-01-25'],
              dtype='datetime64[ns]', freq='D')
```

Date functionality

```
import pandas as pd

df = pd.date_range('01/20/2020', periods=5, freq = 'M')

print(df)
```

```
DatetimeIndex(['2020-01-31', '2020-02-29', '2020-03-31', '2020-04-30',
               '2020-05-31'],
              dtype='datetime64[ns]', freq='M')
```

Time Delta

- Time deltas are differences in times, expressed in difference units, for example, days, hours, minutes, seconds.
- They can be both positive and negative.

Example

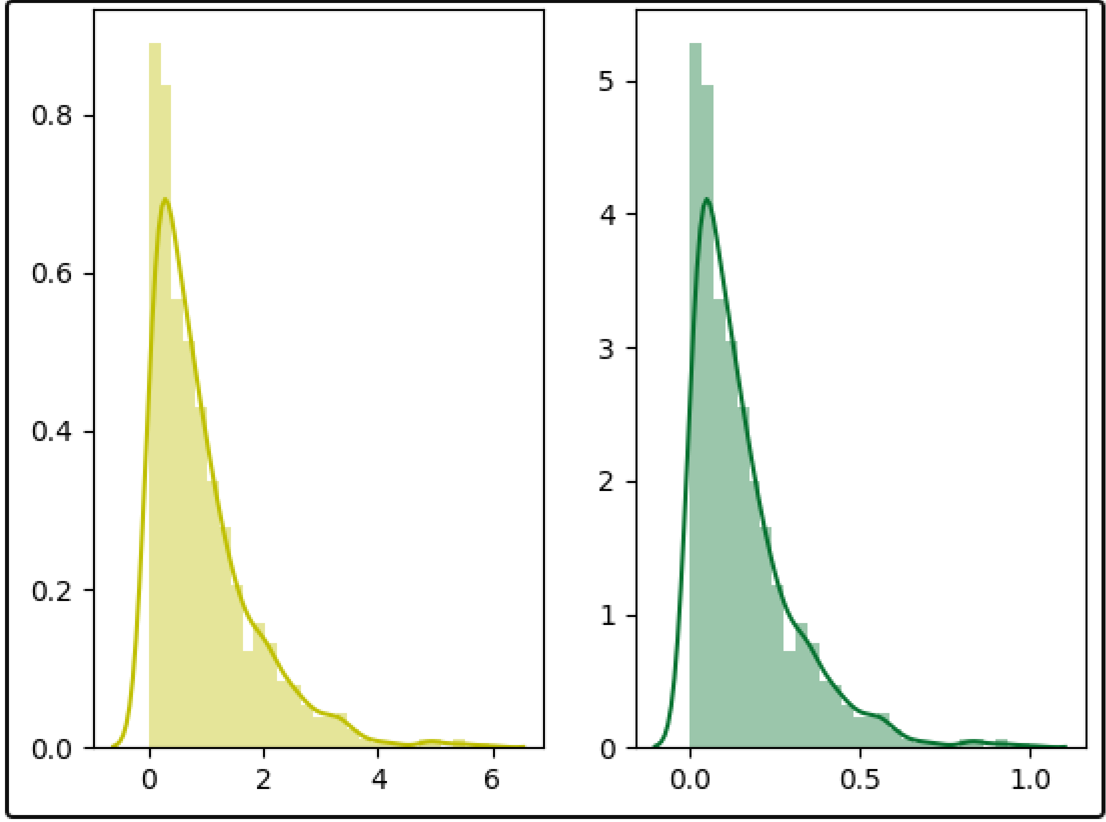
Name	Code	Output
By passing a string literal, we can create a timedelta object.	pd.Timedelta('2 days 2 hours 15 minutes 30 seconds')	2 days 02:15:30
By passing an integer value with the unit, an argument creates a Timedelta object.	pd.Timedelta(6,unit='h')	0 days 06:00:00
Data offsets such as - weeks, days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds	pd.Timedelta(days=2)	2 days 00:00:00
Convert a scalar, array, list, or series from a recognized timedelta format/ value into a Timedelta type. It will construct Series if the input is a Series, a scalar if the input is scalar-like, otherwise will output a TimedeltaIndex.	pd.Timedelta(days=2)	2 days 00:00:00

Example

Name	Code	Output
Operate on Series/ Data Frames and construct timedelta64[ns] Series through subtraction operations on datetime64[ns] Series, or Timestamps.	s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D')) td = pd.Series([pd.Timedelta(days=i) for i in range(3)]) df = pd.DataFrame(dict(A = s, B = td))	A B 0 2012-01-01 0 days 1 2012-01-02 1 days 2 2012-01-03 2 days
Addition Operations	s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D')) td = pd.Series([pd.Timedelta(days=i) for i in range(3)]) df = pd.DataFrame(dict(A = s, B = td)) df['C']=df['A']+df['B']	A B C 0 2012-01-01 0 days 2012-01-01 1 2012-01-02 1 days 2012-01-03 2 2012-01-03 2 days 2012-01-05
Subtraction Operation	s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D')) td = pd.Series([pd.Timedelta(days=i) for i in range(3)]) df = pd.DataFrame(dict(A = s, B = td)) df['C']=df['A']+df['B'] df['D']=df['C']+df['B']	A B C 0 2012-01-01 0 days 2012-01-01 2012-01- 1 2012-01-02 1 days 2012-01-03 2012-01- 2 2012-01-03 2 days 2012-01-05 2012-01-

Normalization

- Normalization refers to rescaling real-valued numeric attributes into a **0 to 1** range.
- Data normalization is used in machine learning to make model training less sensitive to the scale of features. This allows our model to converge to better weights and, in turn, leads to a more accurate model.



Left: Original Data, Right: Normalized Data

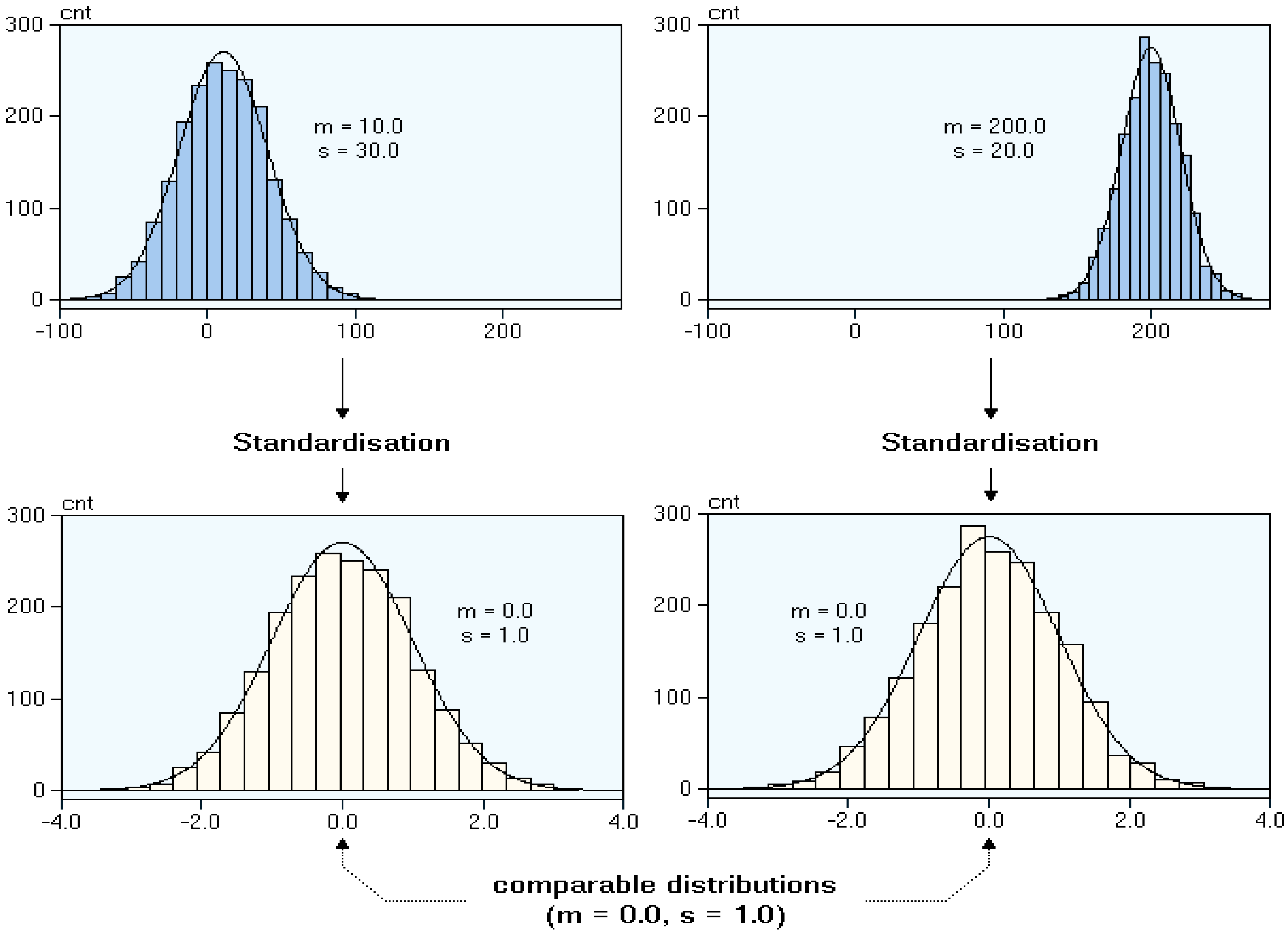
```python
from sklearn import preprocessing
import numpy as np

a = np.random.random((1, 4))
a = a*20
print("Data = ", a)

# normalize the data attributes
normalized = preprocessing.normalize(a)
print("Normalized Data = ", normalized)
```

$$z = \frac{x - \min(x)}{\max(x) - \min(x)}$$

```
Data =  [[10.52384526 14.14223072  9.48558746  2.08542834]]
Normalized Data =  [[0.52288283 0.70266423 0.47129644 0.10361561]]
```

Standardization

$$z = \frac{x_i - \mu}{\sigma}$$



Missing Data Handle

- Missing Data can occur when no information is provided for one or more items or for a whole unit. Missing Data is a very big problem in real life scenario. Missing Data can also refer to as NA(Not Available) values in pandas. In DataFrame sometimes many datasets simply arrive with missing data, either because it exists and was not collected or it never existed.
- In Pandas missing data is represented by two value:
  - **None**: None is a Python singleton object that is often used for missing data in Python code.
  - **NaN** : NaN (an acronym for Not a Number), is a special floating-point value recognized by all systems that use the standard IEEE floating-point representation
- Pandas treat None and NaN as essentially interchangeable for indicating missing or null values. To facilitate this convention, there are several useful functions for detecting, removing, and replacing null values in Pandas DataFrame :
  - **isnull()**
  - **notnull()**
  - **dropna()**
  - **fillna()**
  - **replace()**
  - **interpolate()**

isnull()

```
   First Score  Second Score  Third Score
0        100.0          30.0          NaN
1         90.0          45.0         40.0
2          NaN          56.0         80.0
3         95.0           NaN         98.0
```

	First Score	Second Score	Third Score
0	False	False	True
1	False	False	False
2	True	False	False
3	False	True	False

notnull()

```
   First Score  Second Score  Third Score
0        100.0          30.0          NaN
1         90.0          45.0         40.0
2          NaN          56.0         80.0
3         95.0           NaN         98.0
```

	First Score	Second Score	Third Score
0	True	True	False
1	True	True	True
2	False	True	True
3	True	False	True

Filling Missing Data

	First Score	Second Score	Third Score
0	100.0	30.0	NaN
1	90.0	45.0	40.0
2	NaN	56.0	80.0
3	95.0	NaN	98.0

#1

```
# filling missing value using fillna()
df.fillna(0)
```

	First Score	Second Score	Third Score
0	100.0	30.0	0.0
1	90.0	45.0	40.0
2	0.0	56.0	80.0
3	95.0	0.0	98.0

#2

```
# filling a missing value with
# previous ones
df.fillna(method ='pad')
```

	First Score	Second Score	Third Score
0	100.0	30.0	NaN
1	90.0	45.0	40.0
2	90.0	56.0	80.0
3	95.0	56.0	98.0

#3

```
# filling  null value using fillna() function
df.fillna(method ='bfill')
```

	First Score	Second Score	Third Score
0	100.0	30.0	40.0
1	90.0	45.0	40.0
2	95.0	56.0	80.0
3	95.0	NaN	98.0

Interpolate

	A	B	C	D
0	12.0	NaN	20.0	14.0
1	4.0	2.0	16.0	3.0
2	5.0	54.0	NaN	NaN
3	NaN	3.0	3.0	NaN
4	1.0	NaN	8.0	6.0

	A	B	C	D
0	12.0	NaN	20.0	14.0
1	4.0	2.0	16.0	3.0
2	5.0	54.0	9.5	4.0
3	3.0	3.0	3.0	5.0
4	1.0	3.0	8.0	6.0

dropna()

	First Score	Second Score	Third Score	Fourth Score
0	100.0	30.0	52	NaN
1	90.0	NaN	40	NaN
2	NaN	45.0	80	NaN
3	95.0	56.0	98	65.0

	First Score	Second Score	Third Score	Fourth Score
3	95.0	56.0	98	65.0

dropna()

	First Score	Second Score	Third Score	Fourth Score
0	100.0	30.0	52.0	NaN
1	NaN	NaN	NaN	NaN
2	NaN	45.0	80.0	NaN
3	95.0	56.0	98.0	65.0

	First Score	Second Score	Third Score	Fourth Score
0	100.0	30.0	52.0	NaN
2	NaN	45.0	80.0	NaN
3	95.0	56.0	98.0	65.0

dropna()

	First Score	Second Score	Third Score	Fourth Score
0	100.0	30.0	52.0	60
1	NaN	NaN	NaN	67
2	NaN	45.0	80.0	68
3	95.0	56.0	98.0	65

	Fourth Score
0	60
1	67
2	68
3	65

Window Functions

- .rolling() Function
- .expanding() Function
- .ewm() Function

.rolling() Function

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(10, 4),
index = pd.date_range('1/1/2000', periods=10),
columns = ['A', 'B', 'C', 'D'])

print(df)

print(df.rolling(window=3).mean())
```

```
                   A         B         C         D
2000-01-01 -0.692862 -0.563469 -1.172630  0.062225
2000-01-02  1.013375  1.948667 -0.311838 -0.550377
2000-01-03  0.907432 -2.203215  0.163166  0.099759
2000-01-04  1.416964  0.526772  1.269941 -0.074776
2000-01-05 -1.562144 -0.002639  1.008214 -0.898144
2000-01-06 -0.137106 -0.228348 -1.523341 -0.231084
2000-01-07 -1.023343  1.231910  0.214703 -1.000276
2000-01-08 -0.647357 -1.959665 -0.002584  0.857234
2000-01-09 -0.970856  0.460758 -1.452498  0.642333
2000-01-10 -0.708996 -1.539174 -0.899433 -0.339364
```

```
                   A         B         C         D
2000-01-01       NaN       NaN       NaN       NaN
2000-01-02       NaN       NaN       NaN       NaN
2000-01-03  0.409315 -0.272673 -0.440434 -0.129464
2000-01-04  1.112590  0.090741  0.373756 -0.175131
2000-01-05  0.254084 -0.559694  0.813774 -0.291054
2000-01-06 -0.094095  0.098595  0.251605 -0.401335
2000-01-07 -0.907531  0.333641 -0.100141 -0.709835
2000-01-08 -0.602602 -0.318701 -0.437074 -0.124709
2000-01-09 -0.880519 -0.088999 -0.413460  0.166431
2000-01-10 -0.775736 -1.012694 -0.784838  0.386735
```

.expanding() Function

```
import pandas as pd
import numpy as np

df = pd.DataFrame([
    ['a', 1],
    ['a', 2],
    ['a', 3],
    ['b', 5],
    ['b', 6],
    ['b', 7],
    ['b', 8],
    ['c', 10],
    ['c', 11],
    ['c', 12],
    ['c', 13]
], columns = ['category', 'value'])


print(df)

print(df.value.expanding(min_periods=3).sum())

print(df.value.expanding(min_periods=3).mean())
```

```
   category  value
0         a      1
1         a      2
2         a      3
3         b      5
4         b      6
5         b      7
6         b      8
7         c     10
8         c     11
9         c     12
10        c     13
```

```
0      NaN
1      NaN
2      6.0
3     11.0
4     17.0
5     24.0
6     32.0
7     42.0
8     53.0
9     65.0
10    78.0
Name: value, dtype: float64
```

```
0          NaN
1          NaN
2     2.000000
3     2.750000
4     3.400000
5     4.000000
6     4.571429
7     5.250000
8     5.888889
9     6.500000
10    7.090909
Name: value, dtype: float64
```

EWM

- Ewm is applied on a series of data. Specify any of the com, span, halflife argument and apply the appropriate statistical function on top of it. It assigns the weights exponentially.
- Using to make data smooth to handle noise data

	Stock_ABC_Corp
2020-01-01	12.5
2020-01-02	15.0
2020-01-03	17.0
2020-01-04	10.2
2020-01-05	20.5
2020-01-06	16.1
2020-01-07	14.2
2020-01-08	19.7
2020-01-09	20.0
2020-01-10	2.8

df.ewm(com=0.5).mean()

	Stock_ABC_Corp
2020-01-01	12.500000
2020-01-02	14.375000
2020-01-03	16.192308
2020-01-04	12.147500
2020-01-05	17.738843
2020-01-06	16.644780
2020-01-07	15.014181
2020-01-08	18.138537
2020-01-09	19.379575
2020-01-10	8.326338

Data Analysis in Pandas

Descriptive Statistics

- Most of these are aggregations like sum(), mean(), but some of them, like sumsum(), produce an object of the same size.
- These methods take an axis argument, just like ndarray.{sum, std, ...}, but the axis can be specified by name or integer.
  - DataFrame – “index” (axis=0, default), “columns” (axis=1)

Sr.No.	Function	Description
1	count()	Number of non-null observations
2	sum()	Sum of values
3	mean()	Mean of Values
4	median()	Median of Values
5	mode()	Mode of values
6	std()	Standard Deviation of the Values
7	min()	Minimum Value
8	max()	Maximum Value
9	abs()	Absolute Value
10	prod()	Product of Values
11	cumsum()	Cumulative Sum
12	cumprod()	Cumulative Product

Example

```
#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack',
   'Lee','David','Gasper','Betina','Andres']),
   'Age':pd.Series([25,26,25,23,30,29,23,34,40,30,51,46]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8,3.78,2.98,4.80,4.10,3.65])
}
```

```
#Create a DataFrame
df = pd.DataFrame(d)
print df.sum()
```

```
Age                                                    382
Name      TomJamesRickyVinSteveSmithJackLeeDavidGasperBe...
Rating                                               44.92
dtype: object
```

```
#Create a DataFrame
df = pd.DataFrame(d)
print df.sum(1)
```

```
0     29.23
1     29.24
2     28.98
3     25.56
4     33.20
5     33.60
6     26.80
7     37.78
8     42.98
9     34.80
10    55.10
11    49.65
dtype: float64
```

Summarizing Data

- The describe() function computes a summary of statistics pertaining to the Data Frame columns.

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack',
   'Lee','David','Gasper','Betina','Andres']),
   'Age':pd.Series([25,26,25,23,30,29,23,34,40,30,51,46]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8,3.78,2.98,4.80,4.10,3.65])
}

#Create a DataFrame
df = pd.DataFrame(d)
print df.describe()
```

	Age	Rating
count	12.000000	12.000000
mean	31.833333	3.743333
std	9.232682	0.661628
min	23.000000	2.560000
25%	25.000000	3.230000
50%	29.500000	3.790000
75%	35.500000	4.132500
max	51.000000	4.800000

Summarizing Data with include

- This function gives the mean, std and IQR values. And, function excludes the character columns and given summary about numeric columns. 'include' is the argument which is used to pass necessary information regarding what columns need to be considered for summarizing. Takes the list of values; by default, 'number'.
  - object – Summarizes String columns
  - number – Summarizes Numeric columns
  - all – Summarizes all columns together (Should not pass it as a list value)

describe(include=['object'])

- #Create a DataFrame
- df = pd.DataFrame(d)
- print df.describe(include=['object'])

	Name
count	12
unique	12
top	Ricky
freq	1

describe(include='all')

```
#Create a DataFrame
df = pd.DataFrame(d)
print df. describe(include='all')
```

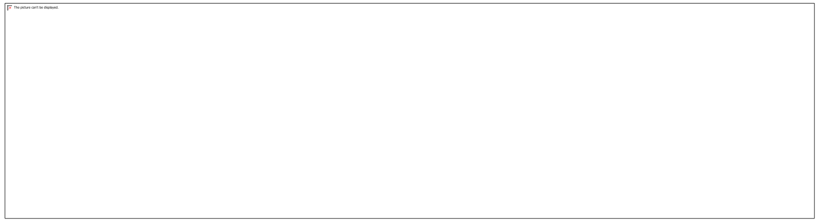
```
              Age     Name     Rating
count   12.000000       12  12.000000
unique        NaN       12        NaN
top           NaN    Ricky        NaN
freq          NaN        1        NaN
mean    31.833333      NaN   3.743333
std      9.232682      NaN   0.661628
min     23.000000      NaN   2.560000
25%     25.000000      NaN   3.230000
50%     29.500000      NaN   3.790000
75%     35.500000      NaN   4.132500
max     51.000000      NaN   4.800000
```

Statistical Functions

- Statistical methods help in the understanding and analyzing the behavior of data.
- Some useful functions:
  - Percent change
  - Covariance
  - Correlation
  - Data Ranking

Percent_change

- Series, DatFrames and Panel, all have the function **pct_change()**.
- This function compares every element with its prior element and computes the change percentage.
- Formulas: $value_n = (x_n - x_{n-1}) : (x_{n-1})$



```
0         NaN
1    1.000000
2    0.500000
3    0.333333
4    0.250000
5   -0.200000
dtype: float64
```

```
df = pd.DataFrame(np.random.randn(5, 2))

print(df)

print(df.pct_change())
```

```
          0         1
0  0.490634 -0.087737
1 -0.642158 -2.015395
2  0.278823 -2.289352
3 -0.937314 -0.828193
4  0.006053 -0.704995
          0          1
0       NaN        NaN
1 -2.308832  21.970813
2 -1.434196   0.135932
3 -4.361687  -0.638241
4 -1.006457  -0.148755
```

Co-variance

- Covariance is applied on **series data**. The Series object has a method **cov** to compute covariance between series objects. **NA** will be excluded automatically.
- The covariance formula is similar to the formula for deals with the calculation of data points from the average value in a dataset. For example, the covariance between two random variables X and Y can be calculated using the following formula (for population → left) or (for sample → right):

$$\mathrm{Cov}(X, Y) = \frac{\sum (X_i - \bar{X})(Y_j - \bar{Y})}{n}$$

$$\mathrm{Cov}(X, Y) = \frac{\sum (X_i - \bar{X})(Y_j - \bar{Y})}{n-1}$$

```python
import pandas as pd
import numpy as np

s1 = pd.Series([1,2,3,4,5,4,1,1,1,2])
s2 = pd.Series([2,2,1,2,3,4,5,6,8,0])

print(s1.cov(s2))
```

→ -1.3555555556

Correlation Value

- The correlation coefficient is a value that indicates the strength of the relationship. The coefficient can take any values from -1 to 1. The interpretations of the values are:
  - **-1:** Perfect negative correlation. The variables tend to move in opposite directions (i.e., when one variable increases, the other variable decreases).
  - **0:** No correlation. The variables do not have a relationship with each other.
  - **1:** Perfect positive correlation. The variables tend to move in the same direction (i.e., when one variable increases, the other variable also increases).

```
import pandas as pd
import numpy as np

frame = pd.DataFrame(np.random.randn(10, 5),
columns=['a', 'b', 'c', 'd', 'e'])

print(frame)

print(" ")

print(frame['a'].corr(frame['b']))

print(" ")

print(frame.corr())
```

	a	b	c	d	e
0	1.420436	0.016242	0.788225	0.326262	-0.590108
1	-1.334494	1.004633	-0.314193	-0.531058	1.523258
2	-0.650768	-0.015261	-1.661331	-0.637942	-1.003861
3	0.146829	-1.498770	-1.044598	0.535980	0.736555
4	0.673129	1.023355	-0.953526	-1.453017	0.885171
5	-0.027378	-1.197029	0.615263	0.185669	-1.108388
6	0.434728	1.874489	0.760801	-0.811918	1.492091
7	0.510840	-0.373273	1.131043	-2.957110	-0.419172
8	-0.257535	0.957575	0.396334	0.303238	-0.952718
9	1.750641	1.061318	0.726307	2.061660	-1.244804

0.074593980183

	a	b	c	d	e
a	1.000000	0.074594	0.473045	0.284992	-0.306381
b	0.074594	1.000000	0.169951	-0.009250	0.330528
c	0.473045	0.169951	1.000000	0.018195	-0.224682
d	0.284992	-0.009250	0.018195	1.000000	-0.336748
e	-0.306381	0.330528	-0.224682	-0.336748	1.000000

Data Ranking

- Data Ranking produces ranking for each element in the array of elements. In case of ties, assigns the mean rank.

```
import pandas as pd
import numpy as np
s = pd.Series([9,0,2,0,3,5,4], index=list('abcdefg'))

print(s)

s['d'] = s['b'] # so there's a tie

print(s.rank())
```

```
a    9
b    0
c    2
d    0
e    3
f    5
g    4
dtype: int64
```

```
a    7.0
b    1.5
c    3.0
d    1.5
e    4.0
f    6.0
g    5.0
dtype: float64
```

Data Ranking – More Example

```
a    9
b    0
c    2
d    0
e    3
f    5
g    4
dtype: int64
```

```
print(s.rank(method = 'min'))

print(s.rank(method = 'max'))

print(s.rank(method = 'first'))
```

```
a    7.0
b    1.0
c    3.0
d    1.0
e    4.0
f    6.0
g    5.0
dtype: float64
a    7.0
b    2.0
c    3.0
d    2.0
e    4.0
f    6.0
g    5.0
dtype: float64
a    7.0
b    1.0
c    3.0
d    2.0
e    4.0
f    6.0
g    5.0
dtype: float64
```

Categorical Data

- Data includes the text columns, which are repetitive. Features like gender, country, and codes are always repetitive. These are the examples for categorical data.
  - Categorical variables can take on only a limited, and usually fixed number of possible values. Besides the fixed length, categorical data might have an order but cannot perform numerical operation. Categorical are a Pandas data type.
  - The categorical data type is useful in the following cases −
    - A **string variable** consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory.
    - The **lexical order of a variable** is not the same as the logical order (“one”, “two”, “three”). By converting to a categorical and specifying an order on the categories, sorting and min/max will use the logical order instead of the lexical order.
    - As a signal to other python libraries that this column should be treated as a **categorical variable** (e.g. to use suitable statistical methods or plot types)

Example

```
import pandas as pd

s = pd.Series(["a","b","c","a"], dtype="category")

print(s)
```

```
0     a
1     b
2     c
3     a
dtype: category
Categories (3, object): [a, b, c]
```

```
cat = cat=pd.Categorical(['a','b','c','a','b','c','d'], ['c', 'b', 'a'])

print(cat)
```

```
[a, b, c, a, b, c, NaN]
Categories (3, object): [c, b, a]
```

Comparison of Categorical Data

```
cat = pd.Series([1,2,3]).astype("category", categories=[1,2,3], ordered=True)
cat1 = pd.Series([2,2,2]).astype("category", categories=[1,2,3], ordered=True)

print(cat>cat1)
```

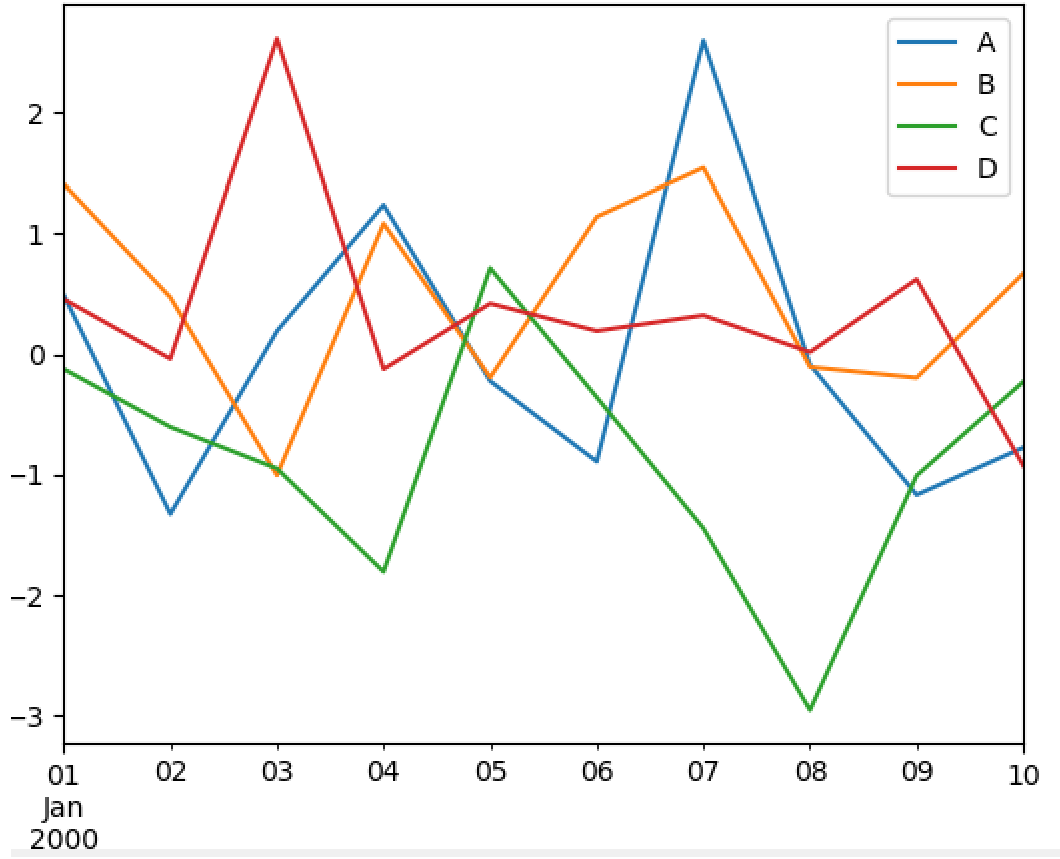
```
0    False
1    False
2     True
dtype: bool
```

Visualization

- Plotting methods allow a handful of plot styles other than the default line plot. These methods can be provided as the kind keyword argument to plot(). These include −
  - bar or barh for bar plots
  - hist for histogram
  - box for boxplot
  - 'area' for area plots
  - 'scatter' for scatter plots

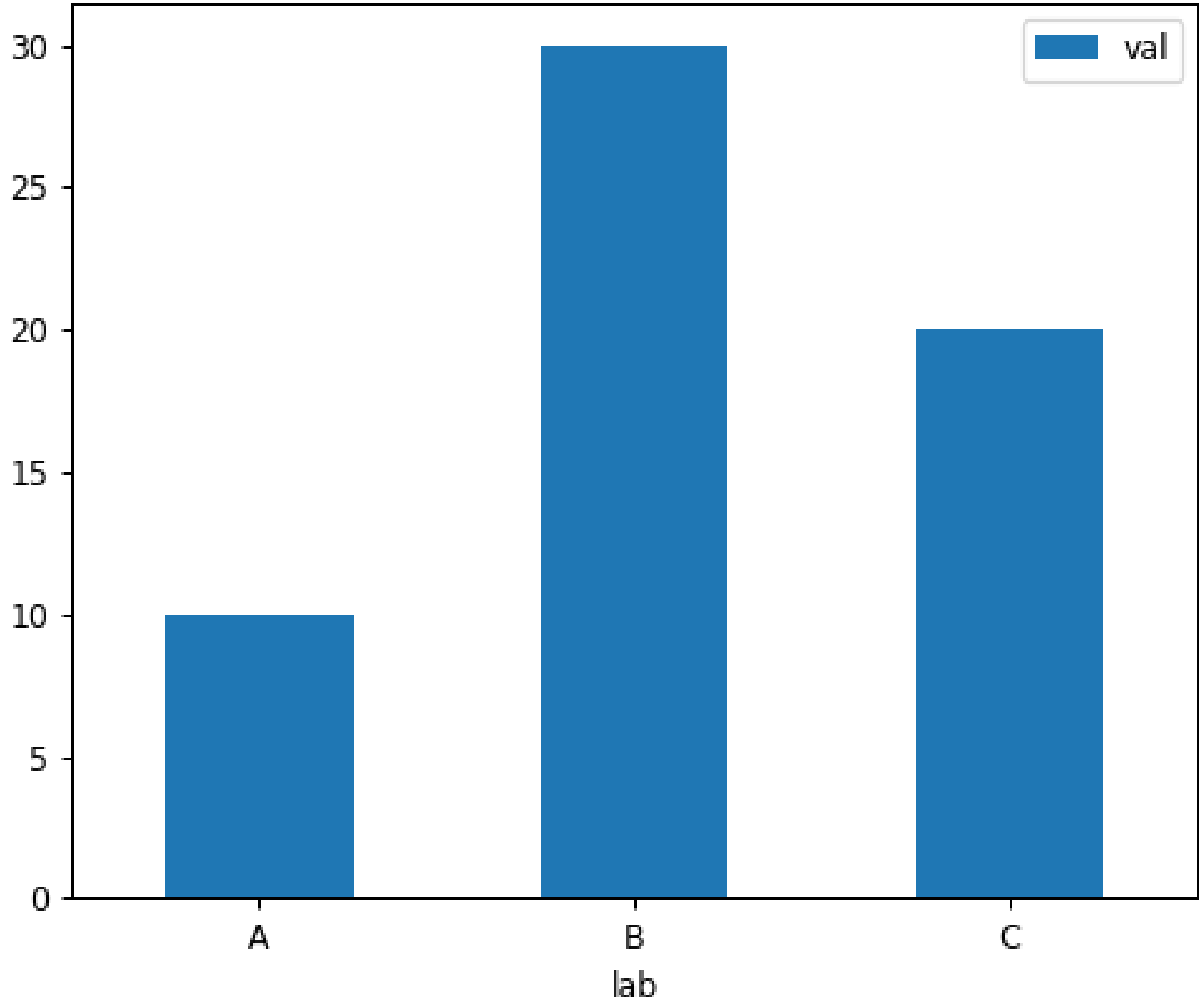
Plotting

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(10,4),
                  index=pd.date_range('1/1/2000',periods=10),
                  columns=list('ABCD'))

df.plot()
```



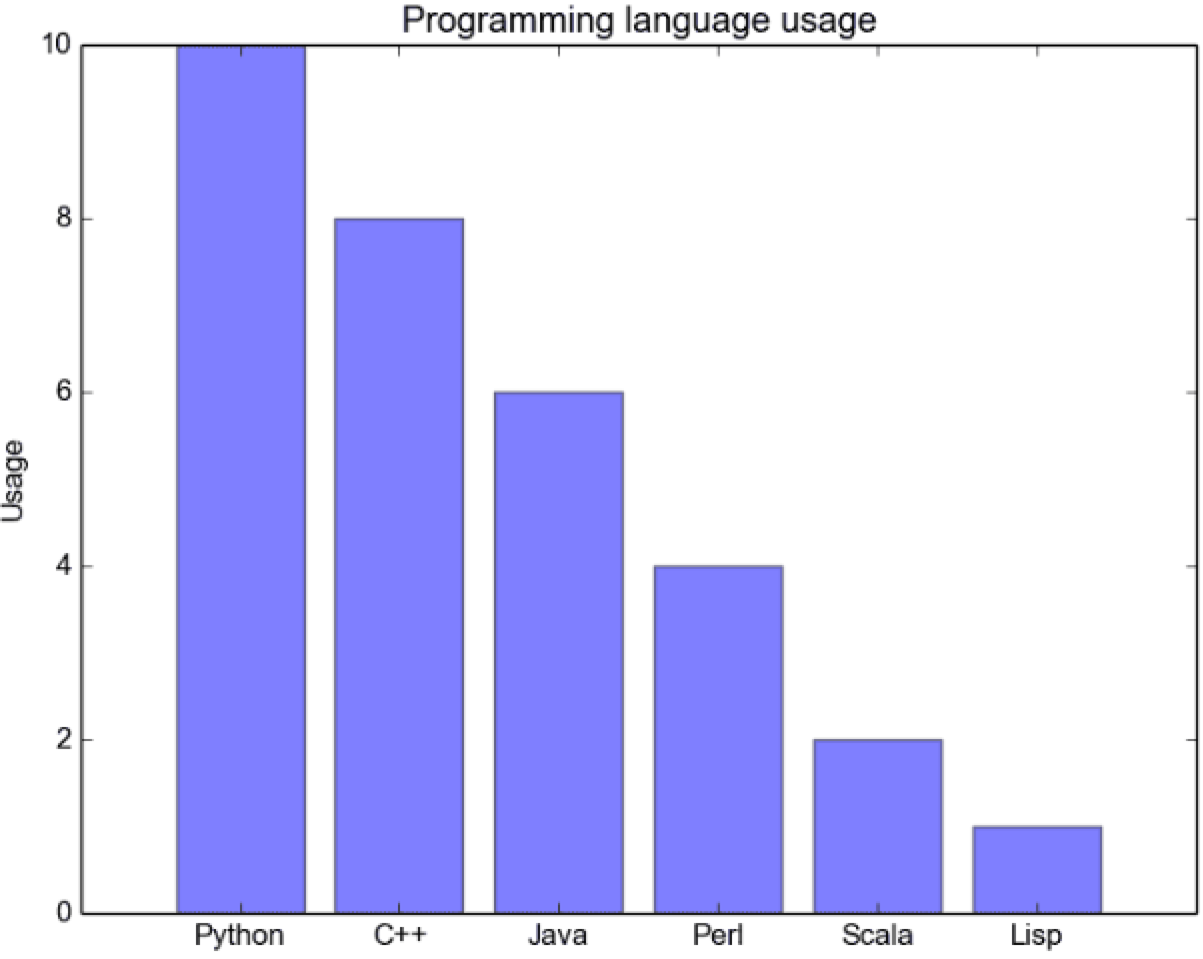
Bar Plotting

```
>>> df = pd.DataFrame({'lab':['A', 'B', 'C'], 'val':[10, 30, 20]})
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```



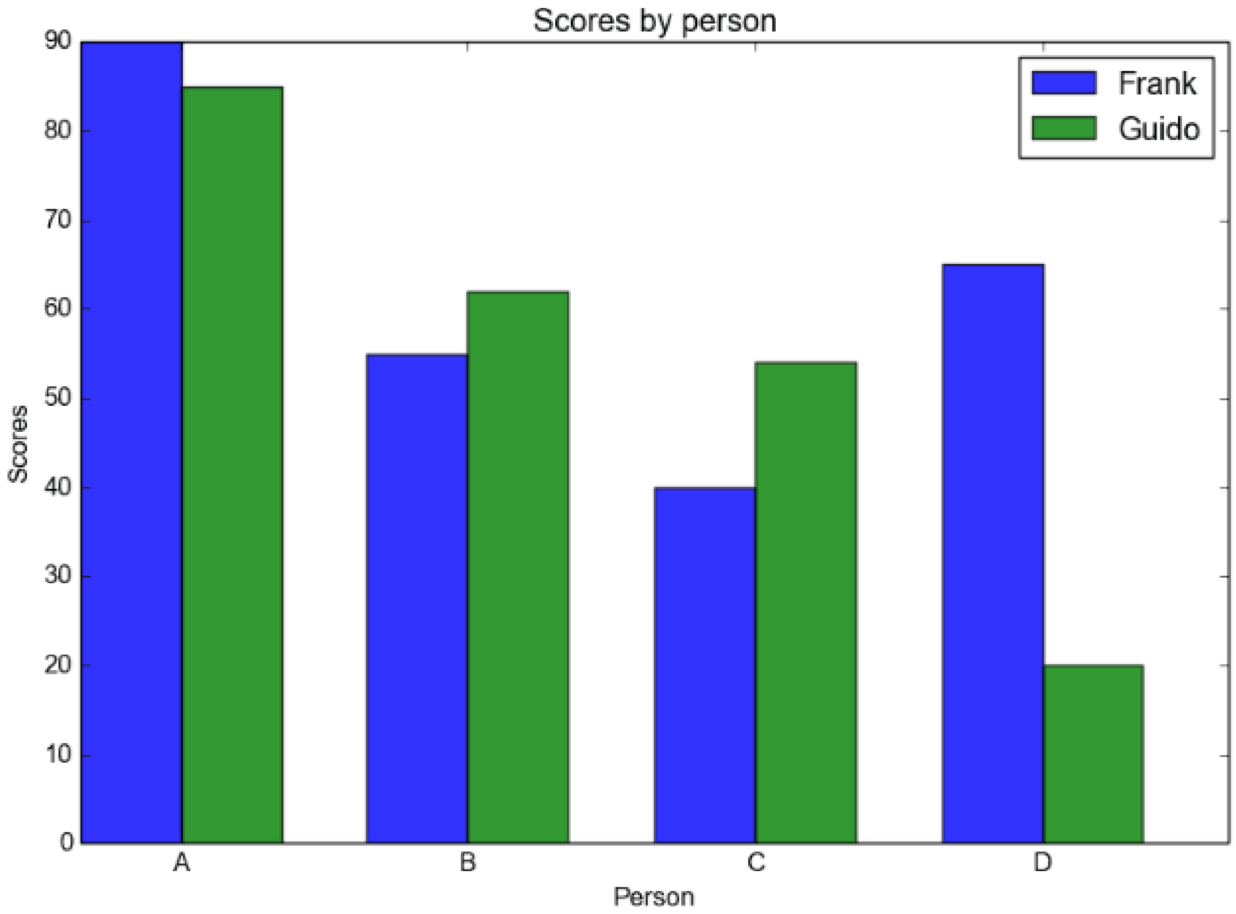
Bar Plotting

```
import matplotlib.pyplot as plt; plt.rcdefaults()
import numpy as np
import matplotlib.pyplot as plt

objects = ('Python', 'C++', 'Java', 'Perl', 'Scala', 'Lisp')
y_pos = np.arange(len(objects))
performance = [10,8,6,4,2,1]

plt.bar(y_pos, performance, align='center', alpha=0.5)
plt.xticks(y_pos, objects)
plt.ylabel('Usage')
plt.title('Programming language usage')

plt.show()
```



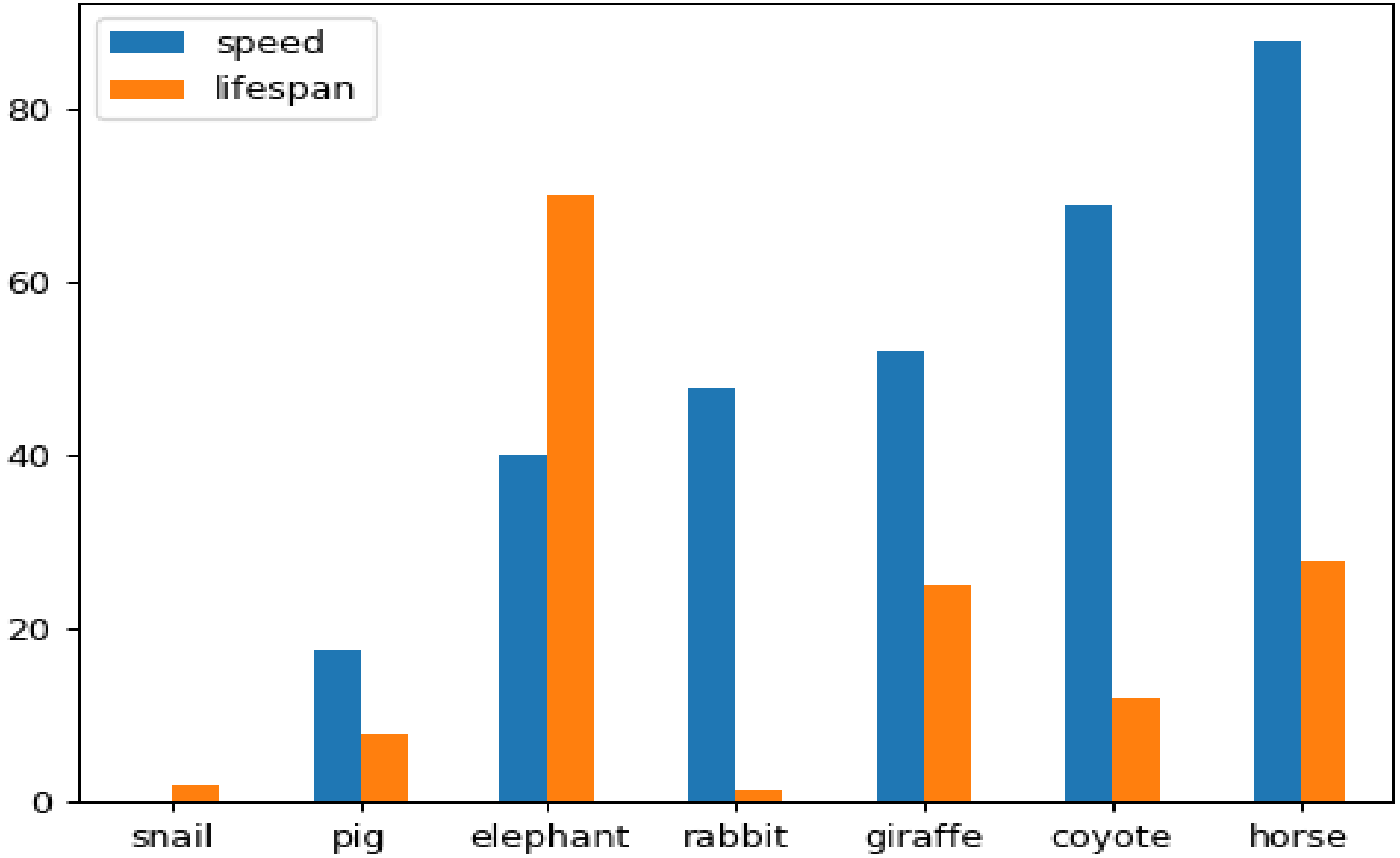
Bar Plotting

```
import numpy as np
import matplotlib.pyplot as plt

# data to plot
n_groups = 4
means_frank = (90, 55, 40, 65)
means_guido = (85, 62, 54, 20)

# create plot
fig, ax = plt.subplots()
index = np.arange(n_groups)
bar_width = 0.35
opacity = 0.8

rects1 = plt.bar(index, means_frank, bar_width,
alpha=opacity,
color='b',
label='Frank')

rects2 = plt.bar(index + bar_width, means_guido, bar_width,
alpha=opacity,
color='g',
label='Guido')

plt.xlabel('Person')
plt.ylabel('Scores')
plt.title('Scores by person')
plt.xticks(index + bar_width, ('A', 'B', 'C', 'D'))
plt.legend()

plt.tight_layout()
plt.show()
```



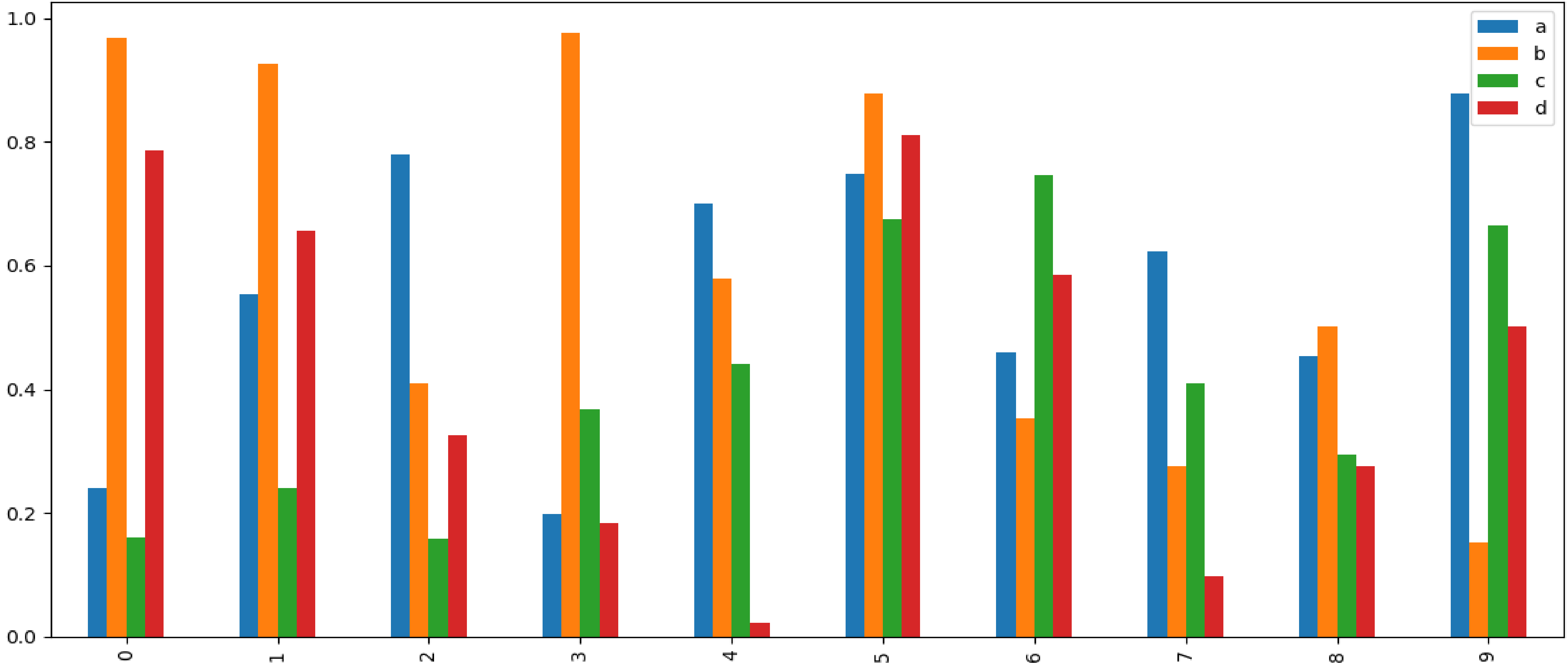
Bar Plotting

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.bar(rot=0)
```



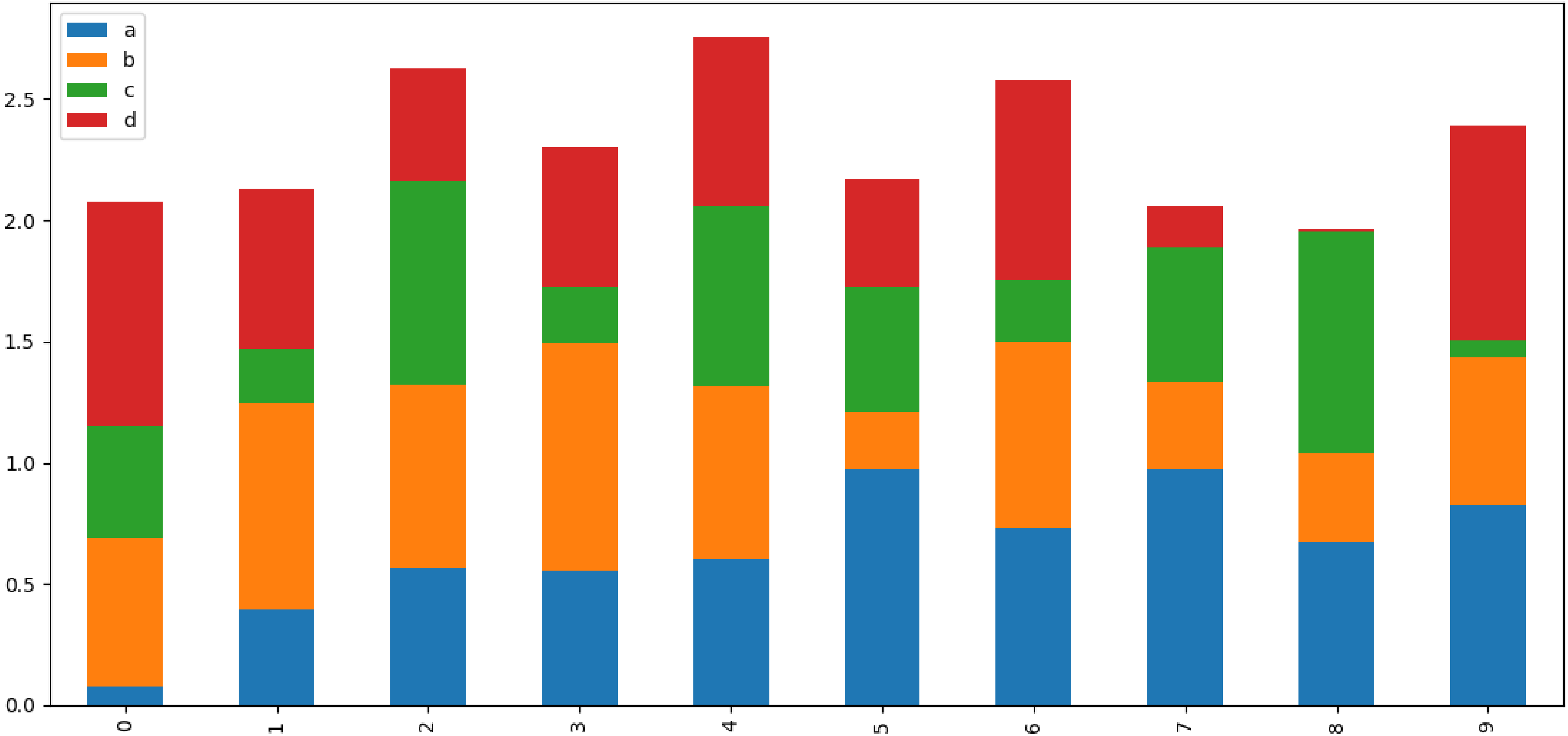
Bar Plotting

```
df = pd.DataFrame(np.random.rand(10,4),columns=['a','b','c','d'])
df.plot.bar()
```



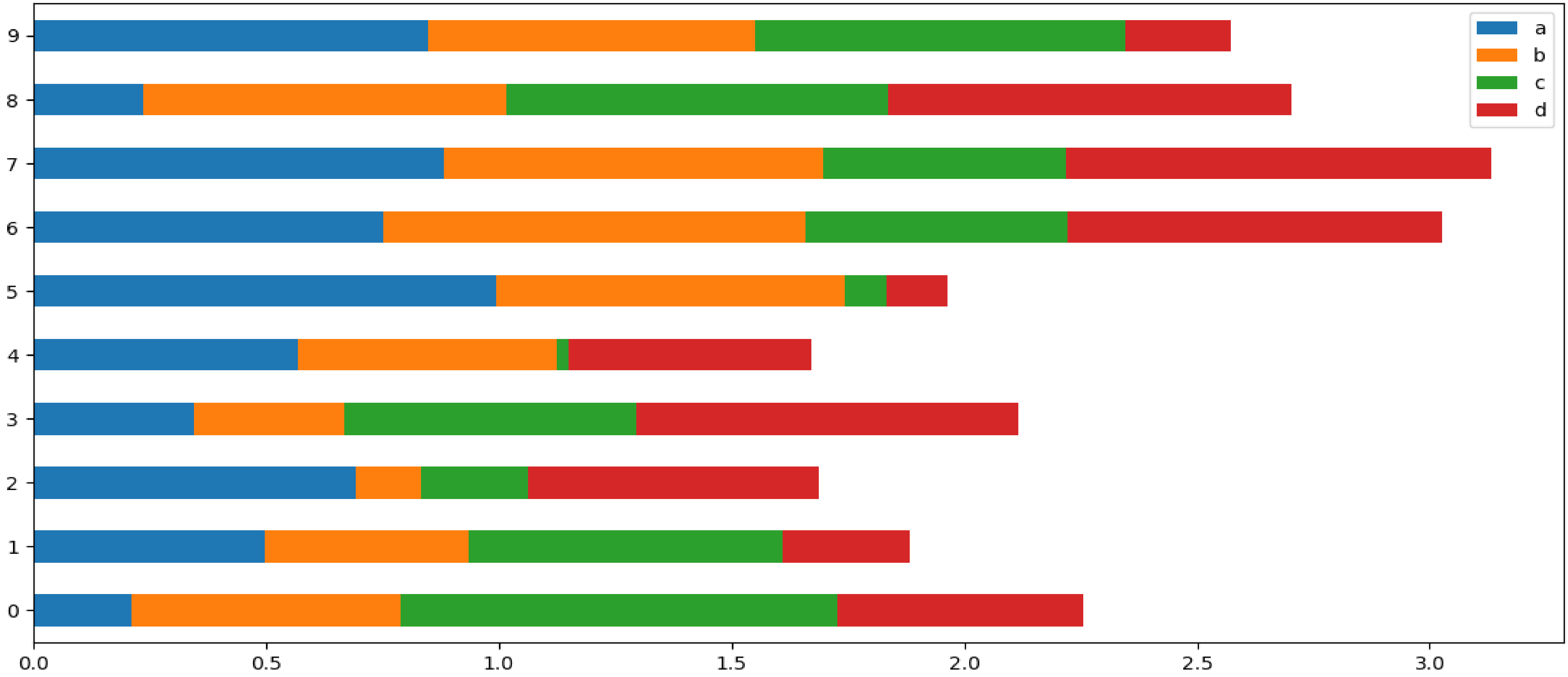
Stacked Bar Plotting

```
df = pd.DataFrame(np.random.rand(10,4),columns=['a','b','c','d'])
df.plot.bar(stacked=True)
```



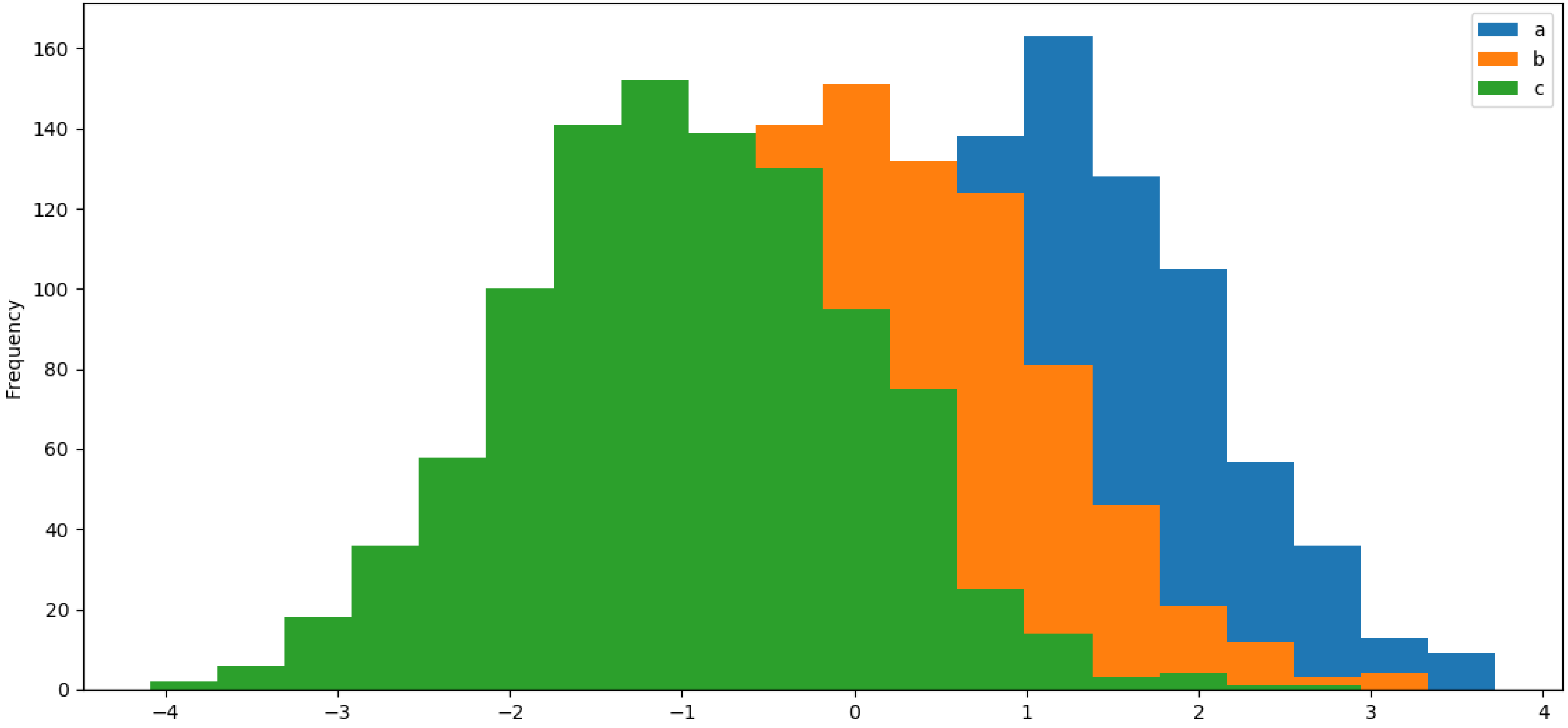
Horizontal Bar Pl

```
df = pd.DataFrame(np.random.rand(10,4),columns=['a','b','c','d'])
df.plot.barh(stacked=True)
```



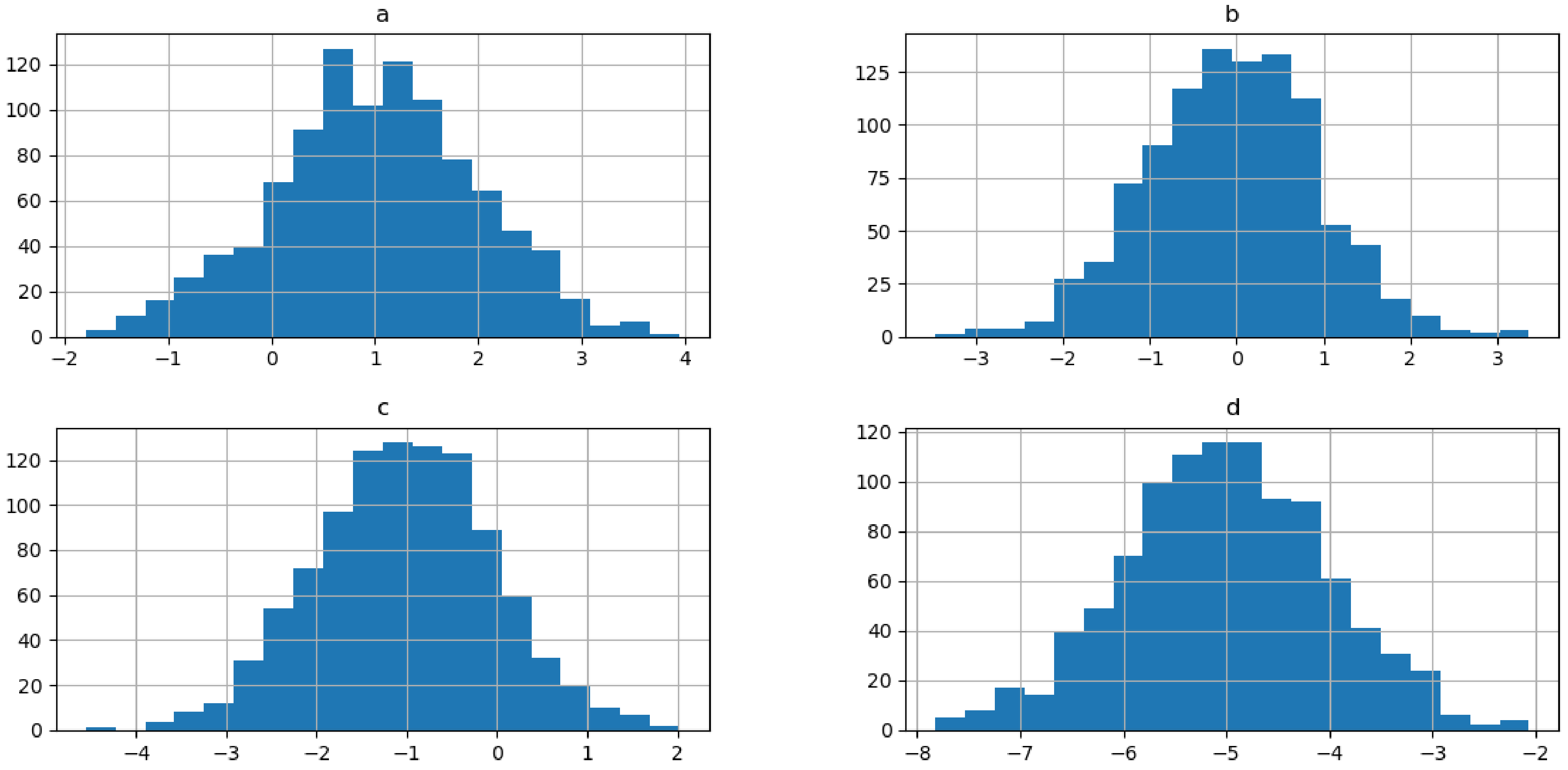
Histogram in same plot

```
df = pd.DataFrame({'a':np.random.randn(1000)+1,'b':np.random.randn(1000),'c':np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])

df.plot.hist(bins=20)
```



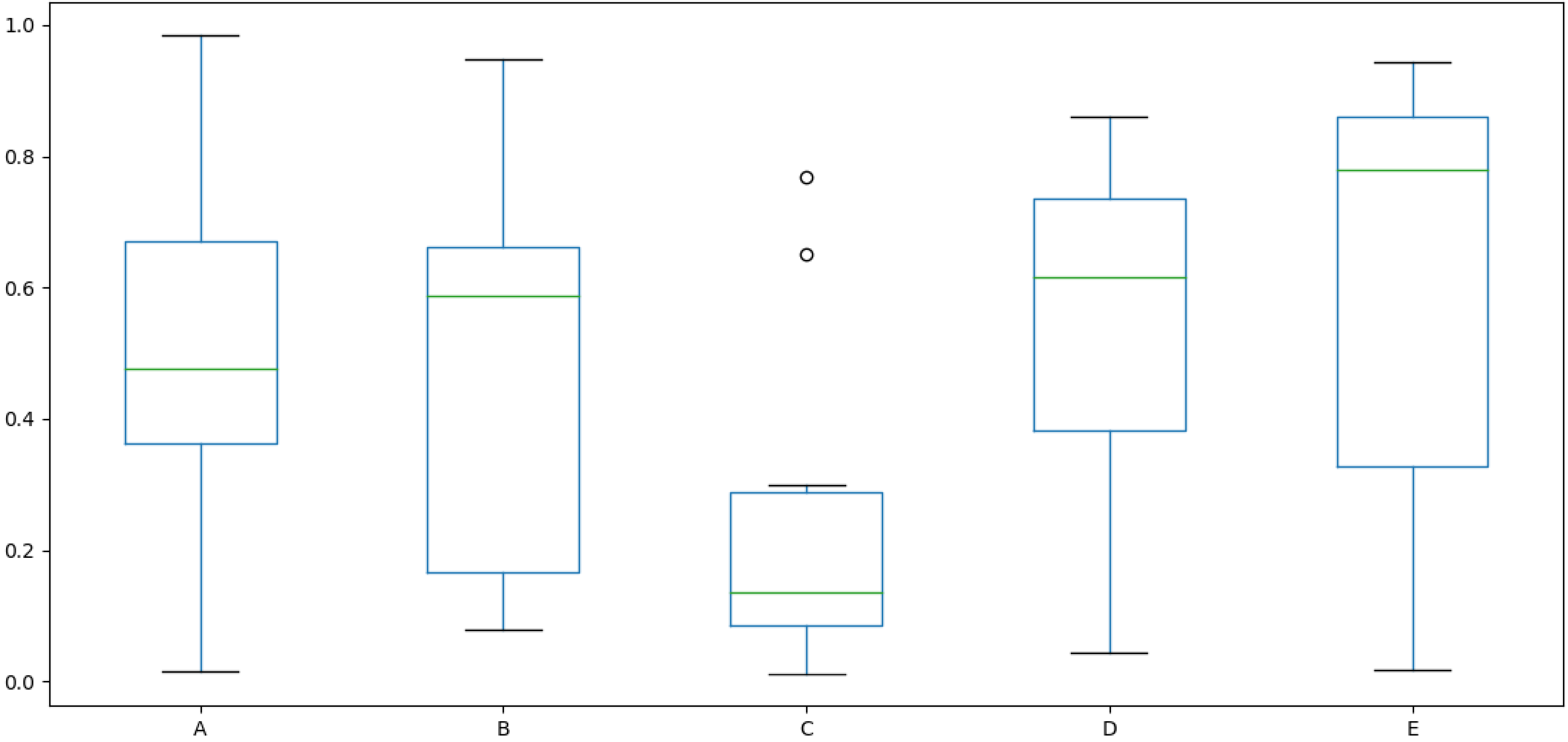
Plot different histograms for each column

```
df=pd.DataFrame({'a':np.random.randn(1000)+1,'b':np.random.randn(1000),
                 'c':np.random.randn(1000) - 1, 'd':np.random.randn(1000) - 5}, columns=['a', 'b', 'c', 'd'])

df.hist(bins=20)
```



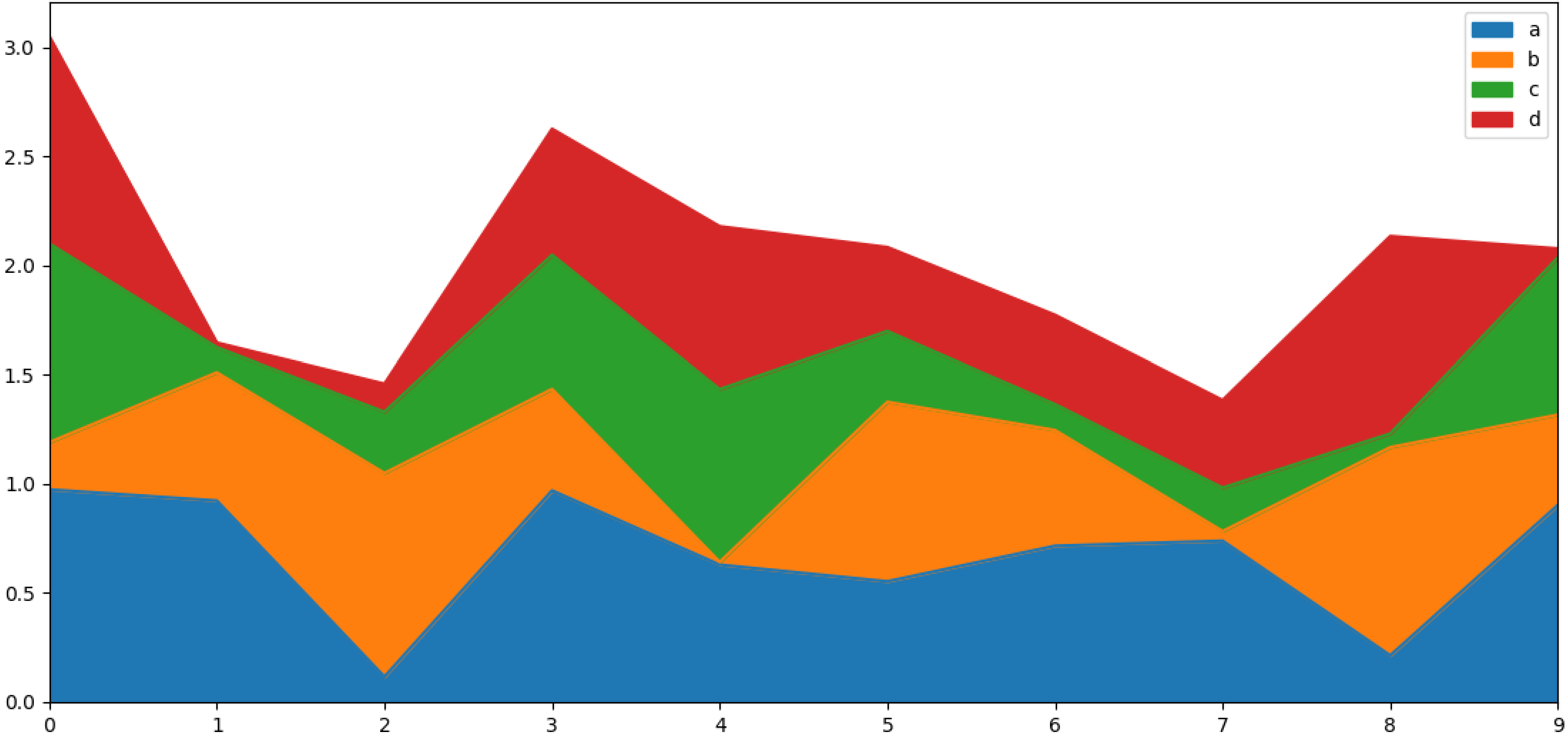
Box Plots

```
df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
df.plot.box()
```



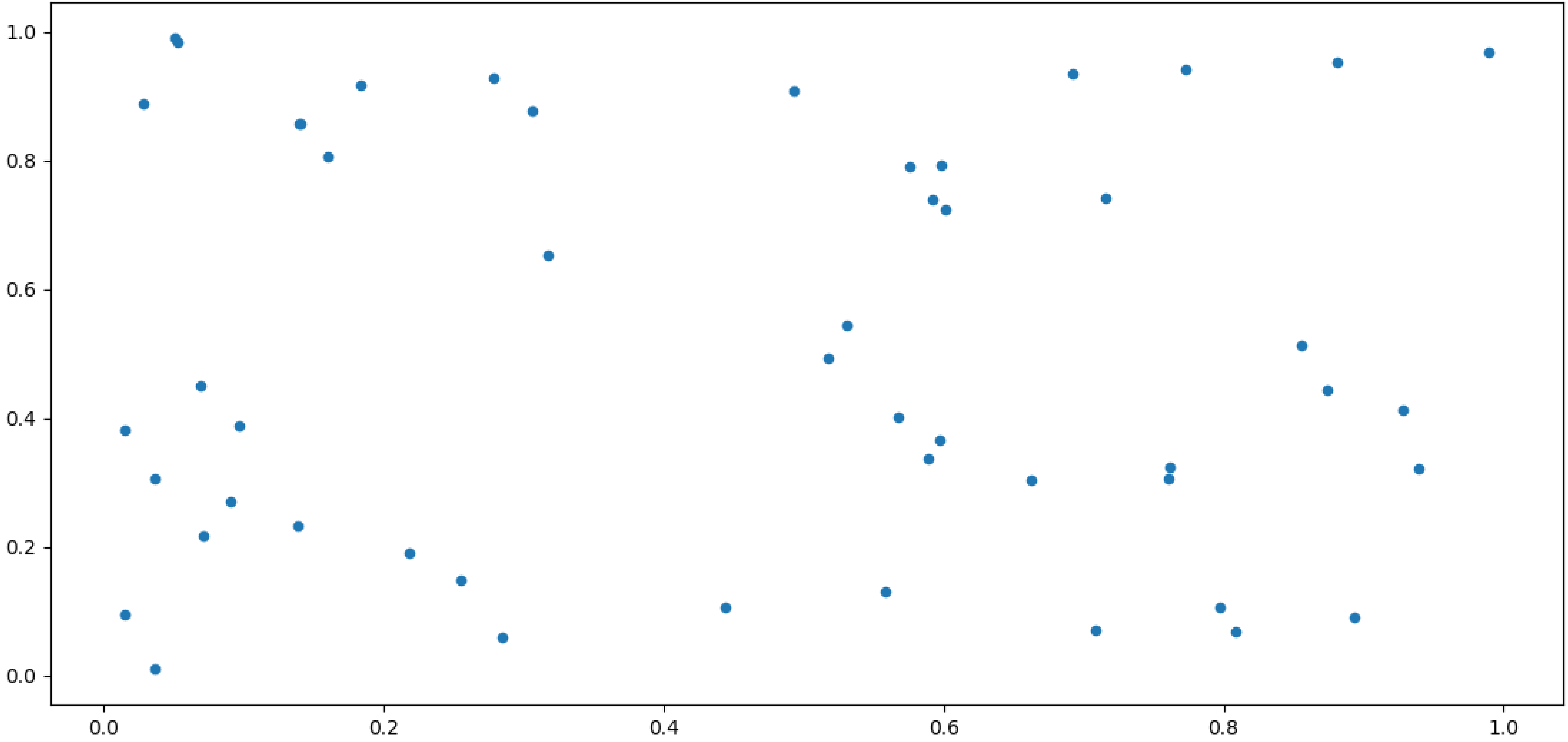
Area Plot

```
df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
df.plot.area()
```



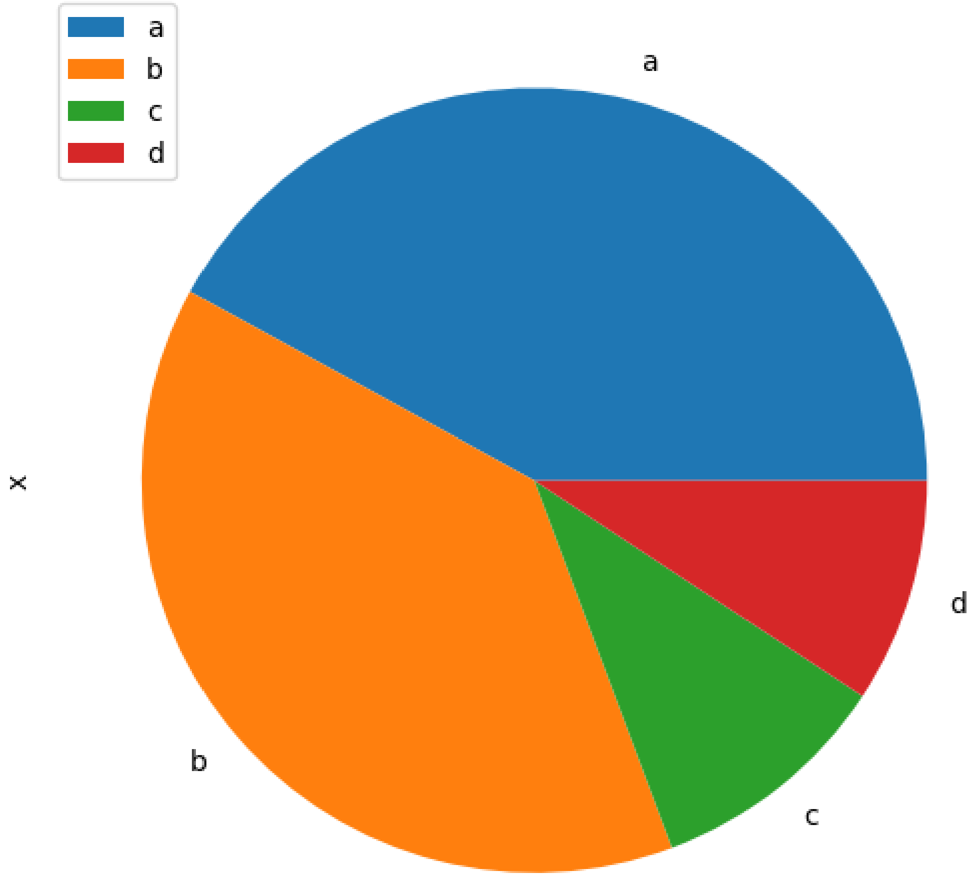
Scatter Plots

```
df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])
df.plot.scatter(x='a', y='b')
```



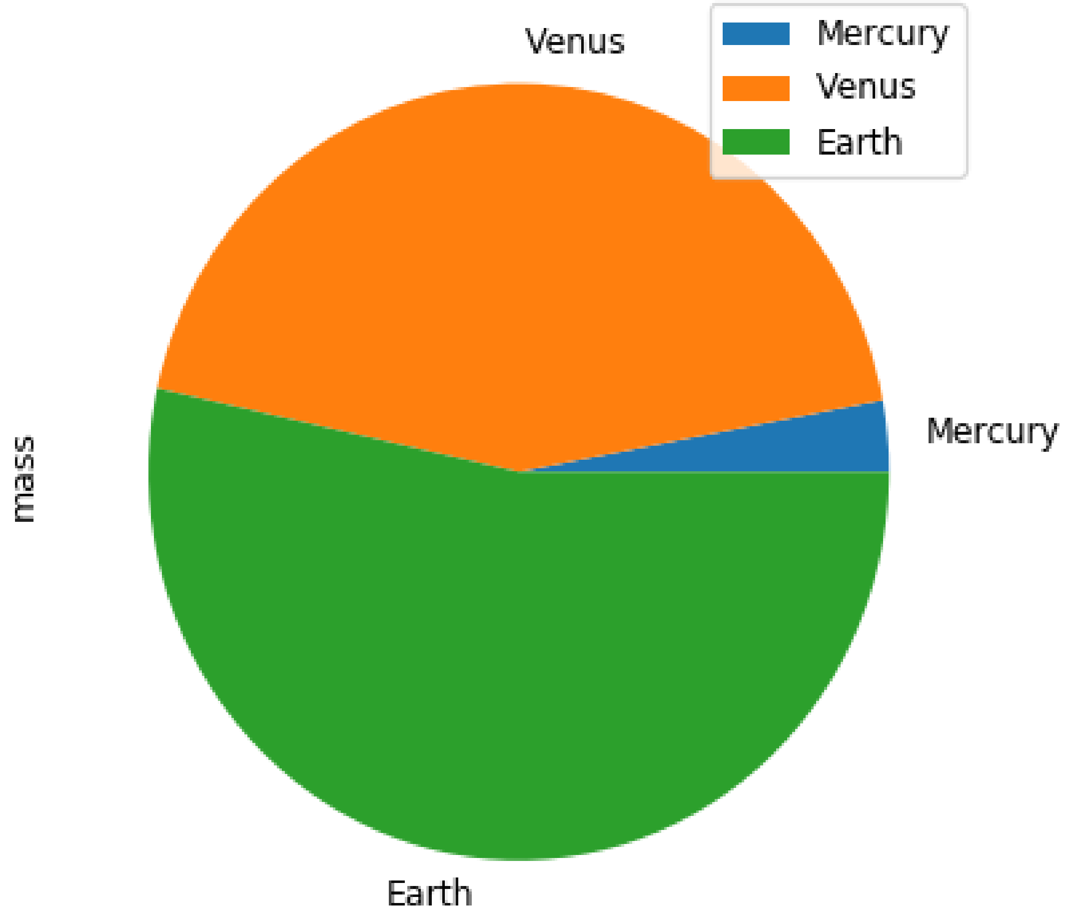
Pie Chart

```
df = pd.DataFrame(3 * np.random.rand(4), index=['a', 'b', 'c', 'd'], columns=['x'])
df.plot.pie(subplots=True)
```



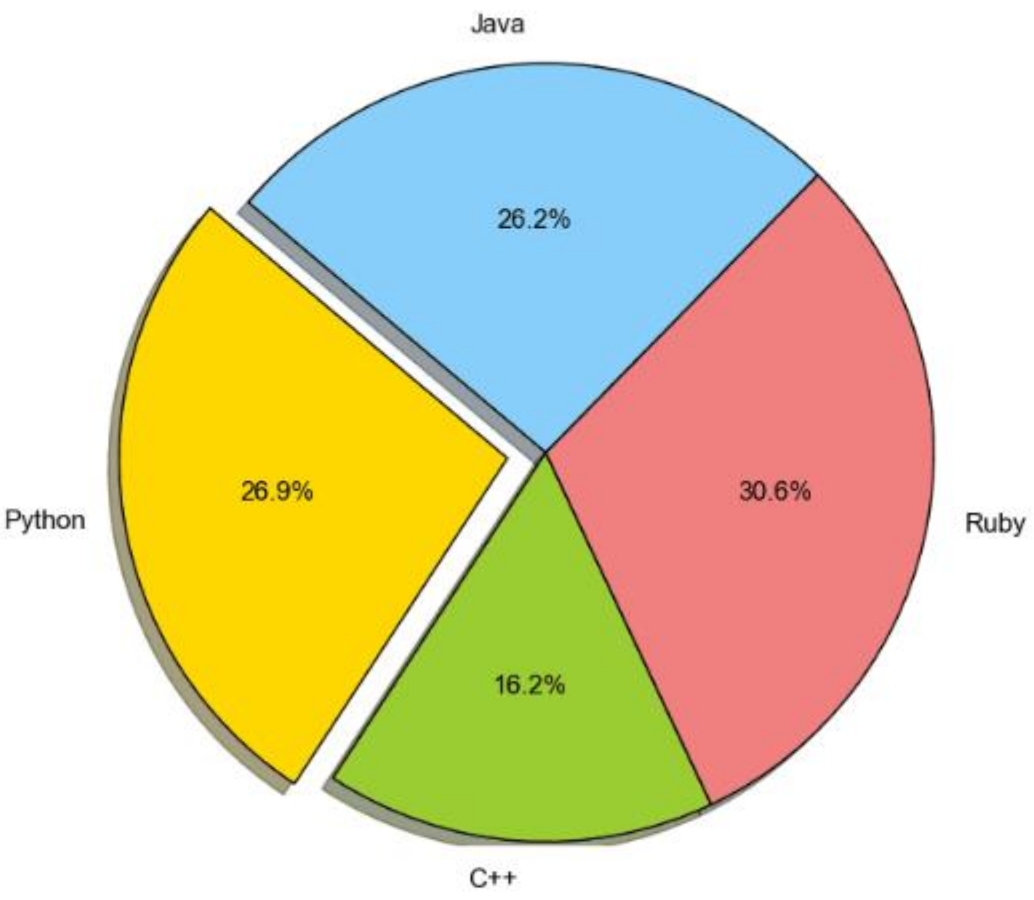
Pie Chart

```
>>> df = pd.DataFrame({'mass': [0.330, 4.87 , 5.97],
...                    'radius': [2439.7, 6051.8, 6378.1]},
...                   index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
```



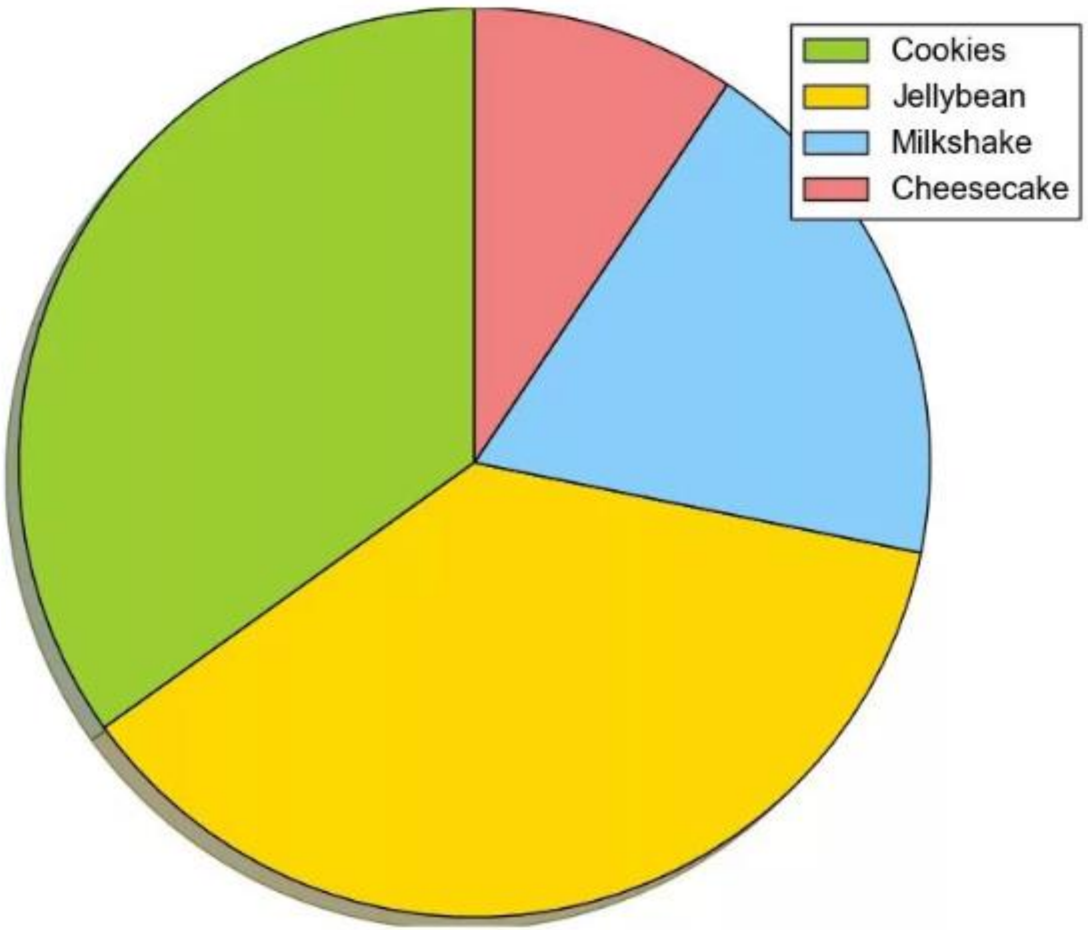
Pie Chart

```
import matplotlib.pyplot as plt

labels = ['Cookies', 'Jellybean', 'Milkshake', 'Cheesecake']
sizes = [38.4, 40.6, 20.7, 10.3]
colors = ['yellowgreen', 'gold', 'lightskyblue', 'lightcoral']
patches, texts = plt.pie(sizes, colors=colors, shadow=True, startangle=90)
plt.legend(patches, labels, loc="best")
plt.axis('equal')
plt.tight_layout()
plt.show()
```



Pie Chart

```
import matplotlib.pyplot as plt

labels = ['Cookies', 'Jellybean', 'Milkshake', 'Cheesecake']
sizes = [38.4, 40.6, 20.7, 10.3]
colors = ['yellowgreen', 'gold', 'lightskyblue', 'lightcoral']
patches, texts = plt.pie(sizes, colors=colors, shadow=True, startangle=90)
plt.legend(patches, labels, loc="best")
plt.axis('equal')
plt.tight_layout()
plt.show()
```



IO Tools

- The two workhorse functions for reading text files (or the flat files) are read_csv() and read_table(). They both use the same parsing code to intelligently convert tabular data into a DataFrame object
- Example: The **temp.csv** file data looks like

```
S.No,Name,Age,City,Salary
1,Tom,28,Toronto,20000
2,Lee,32,HongKong,3000
3,Steven,43,Bay Area,8300
4,Ram,38,Hyderabad,3900
```

```
pandas.read_csv(filepath_or_buffer, sep=',', delimiter=None, header='infer',
names=None, index_col=None, usecols=None
```

```
pandas.read_csv(filepath_or_buffer, sep='\t', delimiter=None, header='infer',
names=None, index_col=None, usecols=None
```

Example

- df=pd.read_csv("temp.csv")
- df=pd.read_csv("temp.csv",index_col=['S.No'])
- df = pd.read_csv("temp.csv", dtype={'Salary': np.float64})
- df=pd.read_csv("temp.csv", names=['a', 'b', 'c','d','e'])

	a	b	c	d	e
0	S.No	Name	Age	City	Salary
1	1	Tom	28	Toronto	20000
2	2	Lee	32	HongKong	3000
3	3	Steven	43	Bay Area	8300
4	4	Ram	38	Hyderabad	3900

df=pd.read_csv("temp.csv",names=['a','b','c','d','e'],header=0)

→ What is about

- df=pd.read_csv("temp.csv", skiprows=2)

	2	Lee	32	HongKong	3000
0	3	Steven	43	Bay Area	8300
1	4	Ram	38	Hyderabad	3900

Sparse Data

- Sparse objects are “compressed” when any data matching a specific value (NaN / missing value, though any value can be chosen) is omitted. A special SparseIndex object tracks where data has been “sparsified”.
- **Using to compress data to improve memory if data is sparse**
- **Use for Series data and Data Frame**
- Sparse data should have the same dtype as its dense representation. Currently, float64, int64 and bool dtypes are supported. Depending on the original dtype, fill_value default changes**.**
  - float64 – np.nan
  - int64 – 0
  - bool – False

Example

	0	1	2	3
0	-0.077609	-0.040412	-0.473463	0.289054
1	-0.991333	0.594367	1.248444	0.498552
2	1.294338	NaN	NaN	NaN
3	-0.259762	NaN	NaN	NaN
4	0.475822	NaN	NaN	NaN
5	-1.868479	NaN	NaN	NaN
6	-3.324342	0.010581	-0.688895	0.141488
7	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN

df.to_sparse() →

compressing

decompressing

← sdf.to_dense()

	0	1	2	3
0	-0.077609	-0.040412	-0.473463	0.289054
1	-0.991333	0.594367	1.248444	0.498552
2	1.294338	NaN	NaN	NaN
3	-0.259762	NaN	NaN	NaN
4	0.475822	NaN	NaN	NaN
5	-1.868479	NaN	NaN	NaN
6	-3.324342	0.010581	-0.688895	0.141488
7	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN

sdf.density → density = 0.4

Caveats & Gotchas

- Caveats means warning and gotcha means an unseen problem.
- Pandas follows the numpy convention of raising an error when you try to convert something to a bool. This happens in an if or when using the Boolean operations, and, or, or not. It is not clear what the result should be. Should it be True because it is not zerolength? False because there are False values? It is unclear, so instead, Pandas raises a ValueError.
- Series data
  - .empty
  - .bool()
  - .item()
  - .any()
  - .all()
  - Bitwise Boolean
  - Isin

Example

```
if pd.Series([False, True, False]).any():
    print("I am any")
```

```
I am any
```

```
print pd.Series([True]).bool()
```

```
True
```

```
s = pd.Series(range(5))
print s==4
```

```
0 False
1 False
2 False
3 False
4 True
dtype: bool
```

```
s = pd.Series(list('abc'))
s = s.isin(['a', 'c', 'e'])
print s
```

```
0 True
1 False
2 True
dtype: bool
```

Comparison with SQL

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

Query	T-SQL	Pandas
SELECT	SELECT total_bill, tip, smoker, time FROM tips LIMIT 5;	tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
WHERE	SELECT * FROM tips WHERE time = 'Dinner' LIMIT 5;	tips[tips['time'] == 'Dinner'].head(5)
GROUP BY	SELECT sex, count(*) FROM tips GROUP BY sex;	tips.groupby('sex').size()
TOP N ROWs	SELECT * FROM tips LIMIT 5 ;	tips.head(5)

Mastering Pandas - To master data manipulation in Python using Pandas, here's what you need to learn:

- read csv
- set index
- reset index
- loc
- iloc
- drop
- dropna
- fillna
- assign
- filter
- query
- rename
- sort values
- agg
- groupby
- concat
- merge
- pivot
- melt

THANK YOU

Q & A