pandas

TUTORIAL FOR BEGINNERS

This Tutorial is aimed at beginners with basic knowledge of Python and no prior experience with pandas to help you get started.

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Python Pandas Tutorial For Beginners : The Ultimate Guide For Beginners

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Pandas is an open-source, BSD-licensed Python library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language. This **Pandas tutorial** has been prepared for those who want to learn about the foundations and advanced features of the Pandas Python package. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc. In this tutorial, we will learn the various features of Python Pandas and how to use them in practice.

What are Pandas?

Pandas is a powerful Python library that is specifically designed to work on data frames that have "relational" or "labelled" data. Its aim aligns with doing real-world data analysis using Python. Its flexibility and functionality make it indispensable for various data-related tasks. Hence, this Python package works well for data manipulation, operating a dataset, exploring a data frame, data analysis, and machine learning-related tasks. To work on it we should first install it using a pip command like "pip install pandas" and then import it like "import pandas as pd". After successfully installing and importing, we can enjoy the innovative functions of pandas to work on datasets or data frames. Pandas versatility and ease of use make it a go-to tool for working with structured data in Python.

Generally, Pandas operates a data frame using Series and DataFrame; where Series works on a one-dimensional labelled array holding data of any type like integers, strings, and objects, while a DataFrame is a two-dimensional data structure that manages and operates data in tabular form (using rows and columns).

Why Pandas?

The beauty of Pandas is that it simplifies the task related to data frames and makes it simple to do many of the time-consuming, repetitive tasks involved in working with data frames, such as:

1. **Import datasets** - available in the form of spreadsheets, comma-separated values (CSV) files, and more.

2. **Data cleansing** - dealing with missing values and representing them as NaN, NA, or NaT.
3. **Size mutability** - columns can be added and removed from DataFrame and higher-dimensional objects.
4. **Data normalisation** – normalise the data into a suitable format for analysis.
5. **Data alignment** - objects can be explicitly aligned to a set of labels.

   Intuitive merging and joining datasets – we can merge and join datasets.
6. **Reshaping and pivoting of datasets** – datasets can be reshaped and pivoted as per the need.
7. **Efficient manipulation and extraction** - manipulation and extraction of specific parts of extensive datasets using intelligent label-based slicing, indexing, and subsetting techniques.
8. **Statistical analysis** - to perform statistical operations on datasets.
9. **Data visualisation** - Visualise datasets and uncover insights.

Applications of Pandas

The most common applications of Pandas are as follows:

1. **Data Cleaning**: Pandas provides functionalities to clean messy data, deal with incomplete or inconsistent data, handle missing values, remove duplicates, and standardise formats to do effective data analysis.
2. **Data Exploration**: Pandas easily summarise statistics, find trends, and visualise data using built-in plotting functions, Matplotlib, or Seaborn integration.
3. **Data Preparation**: Pandas may pivot, melt, convert variables, and merge datasets based on common columns to prepare data for analysis.
4. **Data Analysis**: Pandas supports descriptive statistics, time series analysis, group-by operations, and custom functions.
5. **Data Visualisation**: Pandas itself has basic plotting capabilities; it integrates and supports data visualisation libraries like

Matplotlib, Seaborn, and Plotly to create innovative visualisations.

6. **Time Series Analysis**: Pandas supports date/time indexing, resampling, frequency conversion, and rolling statistics for time series data.
7. **Data Aggregation and Grouping**: Pandas groupby() function lets you aggregate data and compute group-wise summary statistics or apply functions to groups.
8. **Data Input/Output**: Pandas makes data input and export easy by reading and writing CSV, Excel, JSON, SQL databases, and more.
9. **Machine Learning**: Pandas works well with Scikit-learn for data preparation, feature engineering, and model input data.
10. **Web Scraping**: Pandas may be used with BeautifulSoup or Scrapy to parse and analyse structured web data for web scraping and data extraction.
11. **Financial Analysis**: Pandas is commonly used in finance for stock market data analysis, financial indicator calculation, and portfolio optimization.
12. **Text Data Analysis**: Pandas' string manipulation, regular expressions, and text mining functions help analyse textual data.
13. **Experimental Data Analysis**: Pandas makes manipulating and analysing large datasets, performing statistical tests, and visualising results easy.

Audience: Who Should Learn Pandas

This **Pandas tutorial** has been prepared for those who want to learn about the foundations and advanced features of the Pandas Python package. It is most widely used in the domain of data science, engineering, research, agriculture science, management, statistics, and other related fields where computation on a data set requires or explores the data frames to find out the data insights that are required to make fruitful decisions. After completing this tutorial, you will find yourself skilled in pandas Python package from where you can take yourself to the next levels of expertise on other Python packages like Matplotlib, SciPy, scikit-learn, scikit-image, and many more to keep mastering Python language.

Pandas library uses most of the functionalities of NumPy. It is suggested to you to go through our tutorial on NumPy.

Prerequisites To Learn Pandas

You should have a basic understanding of computer programming. A basic understanding of Python and any of the programming languages is a plus. Basic knowledge of statistics and mathematics is helpful for data analysis and interpretation. Pandas provide functions for descriptive statistics, aggregation, and computation of summary metrics. By having a strong foundation of above mentioned, you'll be well-equipped to leverage the power of Pandas for data manipulation and analysis tasks.

Pandas Codebase

You can find the source for the Pandas at https://github.com/jvns/pandas-cookbook

Chapter - 1 : Introduction

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.

In 2008, developer Wes McKinney started developing pandas when in need of a high performance, flexible tool for analysis of data.

Prior to Pandas, Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data — load, prepare, manipulate, model, and analyse.

Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

Key Features of Pandas

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

Chapter - 2 : Environment Setup

Standard Python distribution doesn't come bundled with the Pandas module. A lightweight alternative is to install NumPy using the popular Python package installer, **pip.**

pip install pandas

If you install Anaconda Python package, Pandas will be installed by default with the following −

Windows

1. **Anaconda** (from https://www.continuum.io) is a free Python distribution for SciPy stack. It is also available for Linux and Mac.
2. **Canopy** (https://www.enthought.com/products/canopy/) is available as free as well as commercial distribution with full SciPy stack for Windows, Linux and Mac.
3. **Python** (x,y) is a free Python distribution with SciPy stack and Spyder IDE for Windows OS. (Downloadable from http://python-xy.github.io/)

Linux

Package managers of respective Linux distributions are used to install one or more packages in SciPy stack.

For Ubuntu Users

sudo apt-get install python-numpy python-scipy python-matplotlib ipython ipython notebook
python-pandas python-sympy python-nose

For Fedora Users

sudo yum install numpyscipy python-matplotlibipython python-pandas sympy
python-nose atlas-devel

Chapter - 3 : Introduction to Data Structures

Pandas deals with the following three data structures −

1. Series
2. DataFrame

3. Panel

These data structures are built on top of Numpy arrays, which means they are fast.

Dimension & Description

The best way to think of these data structures is that the higher dimensional data structure is a container of its lower dimensional data structure. For example, DataFrame is a container of Series, Panel is a container of DataFrame.

Data Structure	Dimensions	Description
Series	1	1D labelled homogeneous array, size immutable.
Data Frames	2	General 2D labelled, size-mutable tabular structure with potentially heterogeneously typed columns.
Panel	3	General 3D labelled, size-mutable array.

Building and handling two or more dimensional arrays is a tedious task, the burden is placed on the user to consider the orientation of the data set when writing functions. But using Pandas data structures, the mental effort of the user is reduced.

For example, with tabular data (DataFrame) it is more semantically helpful to think of the **index** (the rows) and the **columns** rather than axis 0 and axis 1.

Mutability

All Pandas data structures are value mutable (can be changed) and except Series all are size mutable. Series is size immutable.

Note − DataFrame is widely used and one of the most important data structures. Panel is used much less.

Series

Series is a one-dimensional array-like structure with homogeneous data. For example, the following series is a collection of integers 10, 23, 56, …

10	23	56	17	52	61	73	90	26	72

Key Points

1. Homogeneous data
2. Size Immutable
3. Values of Data Mutable

DataFrame

DataFrame is a two-dimensional array with heterogeneous data. For example,

Name	**Age**	**Gender**	**Rating**
Steve	32	Male	3.45
Lia	28	Female	4.6
Vin	45	Male	3.9
Katie	38	Female	2.78

The table represents the data of a sales team of an organisation with their overall performance rating. The data is represented in rows and columns. Each column represents an attribute and each row represents a person.

Data Type of Columns

The data types of the four columns are as follows −

Column	Type
Name	String
Age	Integer
Gender	String
Rating	Float

Key Points

1. Heterogeneous data
2. Size Mutable
3. Data Mutable

Panel

Panel is a three-dimensional data structure with heterogeneous data. It is hard to represent the panel in graphical representation. But a panel can be illustrated as a container of DataFrame.

Key Points

1. Heterogeneous data
2. Size Mutable
3. Data Mutable

Chapter - 4 : Python Pandas - Series

Series is a one-dimensional labelled array capable of holding data of any type (integer, string, float, python objects, etc.). The axis labels are collectively called indexes.

pandas.Series

A pandas Series can be created using the following constructor −

pandas.Series(data, index, dtype, copy)

The parameters of the constructor are as follows −

Sr. No	Parameter & Description
1	**data** data takes various forms like ndarray, list, constants
2	**index** Index values must be unique and hashable, same length as data. Default **np.arange(n)** if no index is passed.
3	**dtype** dtype is for data type. If None, data type will be inferred
4	**copy** Copy data. Default False

A series can be created using various inputs like −

1. Array
2. Dict
3. Scalar value or constant

Create an Empty Series

A basic series, which can be created is an Empty Series.

Example

Live Demo

```
#import the pandas library and aliasing as pd
import pandas as pd
s = pd.Series()
print s
```

Its **output** is as follows −

```
Series([], dtype: float64)
```

Create a Series from ndarray

If data is an ndarray, then the index passed must be of the same length. If no index is passed, then by default index will be **range(n)** where **n** is array length, i.e., [0,1,2,3…. **range(len(array))-1].**

Example 1

Live Demo

```
#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
```

Its **output** is as follows −

```
0   a
1   b
2   c
3   d
dtype: object
```

We did not pass any index, so by default, it assigned the indexes ranging from 0 to **len(data)-1**, i.e., 0 to 3.

Example 2

[Live Demo]

```
#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,index=[100,101,102,103])
print s
```

Its **output** is as follows −

```
100  a
101  b
102  c
103  d
dtype: object
```

We passed the index values here. Now we can see the customised indexed values in the output.

Create a Series from dict

A **dict** can be passed as input and if no index is specified, then the dictionary keys are taken in a sorted order to construct the index. If an index is passed, the values in data corresponding to the labels in the index will be pulled out.

Example 1

[Live Demo]

```
#import the pandas library and aliasing as pd
import pandas as pd
import numpy as np
data = {'a' : 0., 'b' : 1., 'c' : 2.}
s = pd.Series(data)
print s
```

Its **output** is as follows −

```
a 0.0
b 1.0
c 2.0
dtype: float64
```

Observe − Dictionary keys are used to construct indexes.

Example 2

Live Demo

```
#import the pandas library and aliasing as pd
import pandas as pd
import numpy as np
data = {'a' : 0., 'b' : 1., 'c' : 2.}
s = pd.Series(data,index=['b','c','d','a'])
print s
```

Its **output** is as follows −

```
b 1.0
c 2.0
d NaN
a 0.0
dtype: float64
```

Observe − Index order is persisted and the missing element is filled with NaN (Not a Number).

Create a Series from Scalar

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

Live Demo

```
#import the pandas library and aliasing as pd
import pandas as pd
import numpy as np
s = pd.Series(5, index=[0, 1, 2, 3])
```

```
print s
```

Its **output** is as follows −

```
0  5
1  5
2  5
3  5
dtype: int64
```

Accessing Data from Series with Position

Data in the series can be accessed similar to that in an **ndarray.**

Example 1

Retrieve the first element. As we already know, the counting starts from zero for the array, which means the first element is stored at zeroth position and so on.

Live Demo

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

#retrieve the first element
print s[0]
```

Its **output** is as follows −

```
1
```

Example 2

Retrieve the first three elements in the Series. If a : is inserted in front of it, all items from that index onwards will be extracted. If two parameters (with : between them) is used, items between the two indexes (not including the stop index)

Live Demo

```
import pandas as pd
```

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

#retrieve the first three element
print s[:3]
```

Its **output** is as follows −

```
a  1
b  2
c  3
dtype: int64
```

Example 3

Retrieve the last three elements.

Live Demo

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

#retrieve the last three element
print s[-3:]
```

Its **output** is as follows −

```
c  3
d  4
e  5
dtype: int64
```

Retrieve Data Using Label (Index)

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

Example 1

Retrieve a single element using index label value.

Live Demo

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

#retrieve a single element
print s['a']
```

Its **output** is as follows −

```
1
```

Example 2

Retrieve multiple elements using a list of index label values.

Live Demo

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

#retrieve multiple elements
print s[['a','c','d']]
```

Its **output** is as follows −

```
a  1
c  3
d  4
dtype: int64
```

Example 3

If a label is not contained, an exception is raised.

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

#retrieve multiple elements
print s['f']
```

Its **output** is as follows −

```
…
```

KeyError: 'f'

Chapter - 5 : DataFrame

A Data frame is a two-dimensional data structure, i.e., data is aligned in a tabular fashion in rows and columns.

Features of DataFrame

1. Potentially columns are of different types
2. Size – Mutable
3. Labelled axes (rows and columns)
4. Can Perform Arithmetic operations on rows and columns

Structure

Let us assume that we are creating a data frame with student’s data.

You can think of it as an SQL table or a spreadsheet data representation.

pandas.DataFrame

A pandas DataFrame can be created using the following constructor −

pandas.DataFrame(data, index, columns, dtype, copy)

The parameters of the constructor are as follows −

Sr. No	Parameter & Description
1	**data**

data takes various forms like ndarray, series, map, lists, dict, constants and also another DataFrame.

2	**index** For the row labels, the Index to be used for the resulting frame is Optional Default np.arange(n) if no index is passed.
3	**columns** For column labels, the optional default syntax is - np.arange(n). This is only true if no index is passed.
4	**dtype** Data type of each column.
5	**copy** This command (or whatever it is) is used for copying data, if the default is False.

Create DataFrame

A pandas DataFrame can be created using various inputs like −

1. Lists
2. dict
3. Series
4. Numpy ndarrays
5. Another DataFrame

In the subsequent sections of this chapter, we will see how to create a DataFrame using these inputs.

Create an Empty DataFrame

A basic DataFrame, which can be created is an Empty Dataframe.

Example

Live Demo

```
#import the pandas library and aliasing as pd
import pandas as pd
df = pd.DataFrame()
print df
```

Its **output** is as follows −

```
Empty DataFrame
Columns: []
Index: []
```

Create a DataFrame from Lists

The DataFrame can be created using a single list or a list of lists.

Example 1

[Live Demo]

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

Its **output** is as follows −

```
     0
0    1
1    2
2    3
3    4
4    5
```

Example 2

[Live Demo]

```
import pandas as pd
data = [['Alex',10],['Bob',12],['Clarke',13]]
df = pd.DataFrame(data,columns=['Name','Age'])
print df
```

Its **output** is as follows −

```
   Name     Age
0  Alex     10
1  Bob      12
2  Clarke   13
```

Example 3

Live Demo

```
import pandas as pd
data = [['Alex',10],['Bob',12],['Clarke',13]]
df = pd.DataFrame(data,columns=['Name','Age'],dtype=float)
print df
```

Its **output** is as follows −

```
   Name     Age
0  Alex     10.0
1  Bob      12.0
2  Clarke   13.0
```

Note − Observe, the **dtype** parameter changes the type of Age column to floating point.

Create a DataFrame from Dict of ndarrays / Lists

All the **ndarrays** must be of the same length. If index is passed, then the length of the index should equal to the length of the arrays.

If no index is passed, then by default, index will be range(n), where **n** is the array length.

Example 1

Live Demo

```
import pandas as pd
data = {'Name':['Tom', 'Jack', 'Steve', 'Ricky'],'Age':[28,34,29,42]}
df = pd.DataFrame(data)
```

```
print df
```

Its **output** is as follows −

```
     Age    Name
0    28     Tom
1    34     Jack
2    29     Steve
3    42     Ricky
```

Note − Observe the values 0,1,2,3. They are the default index assigned to each using the function range(n).

Example 2

Let us now create an indexed DataFrame using arrays.

Live Demo

```
import pandas as pd
data = {'Name':['Tom', 'Jack', 'Steve', 'Ricky'],'Age':[28,34,29,42]}
df = pd.DataFrame(data, index=['rank1','rank2','rank3','rank4'])
print df
```

Its **output** is as follows −

```
         Age    Name
rank 1   28     Tom
rank 2   34     Jack
rank 3   29     Steve
rank 4   42     Ricky
```

Note − Observe, the **index** parameter assigns an index to each row.

Create a DataFrame from List of Dicts

List of Dictionaries can be passed as input data to create a DataFrame. The dictionary keys are by default taken as column names.

Example 1

The following example shows how to create a DataFrame by passing a list of dictionaries.

Live Demo

```
import pandas as pd
data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]
df = pd.DataFrame(data)
print df
```

Its **output** is as follows −

```
    a    b      c
0   1   2     NaN
1   5   10   20.0
```

Note − Observe, NaN (Not a Number) is appended in missing areas.

Example 2

The following example shows how to create a DataFrame by passing a list of dictionaries and the row indices.

Live Demo

```
import pandas as pd
data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]
df = pd.DataFrame(data, index=['first', 'second'])
print df
```

Its **output** is as follows −

```
        a   b       c
first   1   2     NaN
second  5   10   20.0
```

Example 3

The following example shows how to create a DataFrame with a list of dictionaries, row indices, and column indices.

Live Demo

```
import pandas as pd
data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]

#With two column indices, values same as dictionary keys
df1 = pd.DataFrame(data, index=['first', 'second'], columns=['a', 'b'])

#With two column indices with one index with other name
df2 = pd.DataFrame(data, index=['first', 'second'], columns=['a', 'b1'])
print df1
print df2
```

Its **output** is as follows −

```
#df1 output
         a  b
first    1  2
second   5  10

#df2 output
         a  b1
first    1  NaN
second   5  NaN
```

Note − Observe, df2 DataFrame is created with a column index other than the dictionary key; thus, appended the NaN's in place. Whereas, df1 is created with column indices same as dictionary keys, so NaN's appended.

Create a DataFrame from Dict of Series

A Dictionary of Series can be passed to form a DataFrame. The resultant index is the union of all the series indexes passed.

Example

Live Demo

```
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
```

Its **output** is as follows −

```
      one    two
a     1.0    1
b     2.0    2
c     3.0    3
d     NaN    4
```

Note − Observe, for the series one, there is no label **'d'** passed, but in the result, for the **d** label, NaN is appended with NaN.

Let us now understand **column selection, addition**, and **deletion** through examples.

Column Selection

We will understand this by selecting a column from the DataFrame.

Example

Live Demo

```
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 ['one']
```

Its **output** is as follows −

```
a     1.0
b     2.0
c     3.0
d     NaN
Name: one, dtype: float64
```

Column Addition

We will understand this by adding a new column to an existing data frame.

Example

Live Demo

```
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 column label by 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
```

Its **output** is as follows −

```
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

Columns can be deleted or popped; let us take an example to understand how.

Example

Live Demo

```
# 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 data frame 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
```

Its **output** is as follows −

```
Our data frame 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

We will now understand row selection, addition and deletion through examples. Let us begin with the concept of selection.

Selection by Label

Rows can be selected by passing row labels to a **loc** function.

Live Demo

```
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.loc['b']
```

Its **output** is as follows −

```
one 2.0
two 2.0
Name: b, dtype: float64
```

The result is a series with labels as column names of the DataFrame. And, the Name of the series is the label with which it is retrieved.

Selection by integer location

Rows can be selected by passing integer location to an **iloc** function.

Live Demo

```
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.iloc[2]
```

Its **output** is as follows −

```
one   3.0
two   3.0
Name: c, dtype: float64
```

Slice Rows

Multiple rows can be selected using ‘ : ’ operator.

Live Demo

```
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[2:4]
```

Its **output** is as follows −

```
   one  two
c  3.0    3
d  NaN    4
```

Addition of Rows

Add new rows to a DataFrame using the **append** function. This function will append the rows at the end.

Live Demo

```
import pandas as pd

df = pd.DataFrame([[1, 2], [3, 4]], columns = ['a','b'])
df2 = pd.DataFrame([[5, 6], [7, 8]], columns = ['a','b'])

df = df.append(df2)
print df
```

Its **output** is as follows −

```
   a  b
0  1  2
1  3  4
0  5  6
1  7  8
```

Deletion of Rows

Use index labels to delete or drop rows from a DataFrame. If the label is duplicated, then multiple rows will be dropped.

If you observe, in the above example, the labels are duplicate. Let us drop a label and see how many rows will get dropped.

Live Demo

```
import pandas as pd

df = pd.DataFrame([[1, 2], [3, 4]], columns = ['a','b'])
df2 = pd.DataFrame([[5, 6], [7, 8]], columns = ['a','b'])

df = df.append(df2)

# Drop rows with label 0
df = df.drop(0)

print df
```

Its **output** is as follows −

```
 a b
1 3 4
1 7 8
```

In the above example, two rows were dropped because those two contain the same label 0.

Chapter - 6 : Panel

A **panel** is a 3D container of data. The term **Panel data** is derived from econometrics and is partially responsible for the name pandas − **pan(el)-da(ta)**-s.

The names for the 3 axes are intended to give some semantic meaning to describing operations involving panel data. They are −

1. **items** − axis 0, each item corresponds to a DataFrame contained inside.
2. **major_axis** − axis 1, it is the index (rows) of each of the DataFrames.
3. **minor_axis** − axis 2, it is the columns of each of the DataFrames.

pandas.Panel()

A Panel can be created using the following constructor −

```
pandas.Panel(data, items, major_axis, minor_axis, dtype, copy)
```

The parameters of the constructor are as follows −

Parameter	**Description**

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**

Create Panel

A Panel can be created using multiple ways like −

- From ndarrays
- From dict of DataFrames

From 3D ndarray

Live Demo

```
# 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
```

Its **output** is as follows −

```
<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

Note − Observe the dimensions of the empty panel and the above panel, all the objects are different.

From dict of DataFrame Objects

Live Demo

```
#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
```

Its **output** is as follows −

```
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
```

Create an Empty Panel

An empty panel can be created using the Panel constructor as follows −

Live Demo

```
#creating an empty panel
import pandas as pd
p = pd.Panel()
print p
```

Its **output** is as follows −

```
<class 'pandas.core.panel.Panel'>
Dimensions: 0 (items) x 0 (major_axis) x 0 (minor_axis)
Items axis: None
Major_axis axis: None
```

Minor_axis axis: None

Selecting the Data from Panel

Select the data from the panel using −

1. Items
2. Major_axis
3. Minor_axis

Using Items

Live Demo

```
# 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['Item1']
```

Its **output** is as follows −

```
            0          1          2
0    0.488224  -0.128637   0.930817
1    0.417497   0.896681   0.576657
2   -2.775266   0.571668   0.290082
3   -0.400538  -0.144234   1.110535
```

We have two items, and we retrieved item1. The result is a DataFrame with 4 rows and 3 columns, which are the **Major_axis** and **Minor_axis** dimensions.

Using major_axis

Data can be accessed using the method **panel.major_axis(index)**.

Live Demo

```
# 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.major_xs(1)
```

Its **output** is as follows −

```
      Item1       Item2
0   0.417497    0.748412
1   0.896681   -0.557322
2   0.576657       NaN
```

Using minor_axis

Data can be accessed using the method **panel.minor_axis(index).**

Live Demo

```
# 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.minor_xs(1)
```

Its **output** is as follows −

```
       Item1       Item2
0   -0.128637   -1.047032
1    0.896681   -0.557322
2    0.571668    0.431953
3   -0.144234    1.302466
```

Note − Observe the changes in the dimensions.

Chapter - 7 : Basic Functionality

By now, we learnt about the three Pandas DataStructures and how to create them. We will majorly focus on the DataFrame objects because of its importance in the real time data processing and also discuss a few other DataStructures.

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 the series is empty.
4	**ndim** Returns the number of dimensions of the underlying data, by definition 1.
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.

Let us now create a Series and see all the above tabulated attributes operation.

Example

Live Demo

```
import pandas as pd
import numpy as np

#Create a series with 100 random numbers
s = pd.Series(np.random.randn(4))
print s
```

Its **output** is as follows −

```
0   0.967853
1  -0.148368
2  -1.395906
3  -1.758394
dtype: float64
```

axes

Returns the list of the labels of the series.

Live Demo

```
import pandas as pd
import numpy as np

#Create a series with 100 random numbers
s = pd.Series(np.random.randn(4))
print ("The axes are:")
print s.axes
```

Its **output** is as follows −

```
The axes are:
[RangeIndex(start=0, stop=4, step=1)]
```

The above result is a compact format of a list of values from 0 to 5, i.e., [0,1,2,3,4].

empty

Returns the Boolean value saying whether the Object is empty or not. True indicates that the object is empty.

Live Demo

```
import pandas as pd
import numpy as np

#Create a series with 100 random numbers
s = pd.Series(np.random.randn(4))
print ("Is the Object empty?")
print s.empty
```

Its **output** is as follows −

```
Is the Object empty?
False
```

ndim

Returns the number of dimensions of the object. By definition, a Series is a 1D data structure, so it returns

Live Demo

```
import pandas as pd
import numpy as np

#Create a series with 4 random numbers
s = pd.Series(np.random.randn(4))
print s

print ("The dimensions of the object:")
print s.ndim
```

Its **output** is as follows −

```
0   0.175898
```

```
1   0.166197
2  -0.609712
3  -1.377000
dtype: float64

The dimensions of the object:
1
```

size

Returns the size(length) of the series.

Live Demo

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

#Create a series with 4 random numbers
s = pd.Series(np.random.randn(2))
print s
print ("The size of the object:")
print s.size
```

Its **output** is as follows −

```
0   3.078058
1  -1.207803
dtype: float64

The size of the object:
2
```

values

Returns the actual data in the series as an array.

Live Demo

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

```
#Create a series with 4 random numbers
s = pd.Series(np.random.randn(4))
print s

print ("The actual data series is:")
print s.values
```

Its **output** is as follows −

```
0   1.787373
1  -0.605159
2   0.180477
3  -0.140922
dtype: float64

The actual data series is:
[ 1.78737302 -0.60515881 0.18047664 -0.1409218 ]
```

Head & Tail

To view a small sample of a Series or the DataFrame object, use the head() and the tail() methods.

head() returns the first **n** rows(observe the index values). The default number of elements to display is five, but you may pass a custom number.

Live Demo

```
import pandas as pd
import numpy as np

#Create a series with 4 random numbers
s = pd.Series(np.random.randn(4))
print ("The original series is:")
print s

print ("The first two rows of the data series:")
print s.head(2)
```

Its **output** is as follows −

```
The original series is:
0   0.720876
1  -0.765898
2   0.479221
3  -0.139547
dtype: float64

The first two rows of the data series:
0   0.720876
1  -0.765898
dtype: float64
```

tail() returns the last **n** rows(observe the index values). The default number of elements to display is five, but you may pass a custom number.

Live Demo

```
import pandas as pd
import numpy as np

#Create a series with 4 random numbers
s = pd.Series(np.random.randn(4))
print ("The original series is:")
print s

print ("The last two rows of the data series:")
print s.tail(2)
```

Its **output** is as follows −

```
The original series is:
0 -0.655091
1 -0.881407
2 -0.608592
3 -2.341413
dtype: float64

The last two rows of the data series:
2 -0.608592
3 -2.341413
```

dtype: float64

DataFrame Basic Functionality

Let us now understand what DataFrame Basic Functionality is. The following tables list down the important attributes or methods that help in 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.
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.

Let us now create a DataFrame and see all how the above mentioned attributes operate.

Example

[Live Demo](#)

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our data series is:")
print df
```

Its **output** is as follows −

```
Our data series is:
    Age   Name    Rating
0   25    Tom     4.23
1   26    James   3.24
2   25    Ricky   3.98
3   23    Vin     2.56
4   30    Steve   3.20
5   29    Smith   4.60
6   23    Jack    3.80
```

T (Transpose)

Returns the transpose of the DataFrame. The rows and columns will interchange.

Live Demo

```
import pandas as pd
import numpy as np

# Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

# Create a DataFrame
df = pd.DataFrame(d)
print ("The transpose of the data series is:")
print df.T
```

Its **output** is as follows −

```
The transpose of the data series is:
          0     1       2      3      4      5       6
Age      25    26      25     23     30     29      23
Name     Tom   James   Ricky  Vin    Steve  Smith   Jack
Rating   4.23  3.24    3.98   2.56   3.2    4.6     3.8
```

axes

Returns the list of row axis labels and column axis labels.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
```

```
df = pd.DataFrame(d)
print ("Row axis labels and column axis labels are:")
print df.axes
```

Its **output** is as follows −

Row axis labels and column axis labels are:

[RangeIndex(start=0, stop=7, step=1), Index([usAge', u'Name', u Rating'], dtype='object')]

dtypes

Returns the data type of each column.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("The data types of each column are:")
print df.dtypes
```

Its **output** is as follows −

```
The data types of each column are:
Age     int64
Name    object
Rating  float64
dtype: object
```

empty

Returns the Boolean value saying whether the Object is empty or not; True indicates that the object is empty.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Is the object empty?")
print df.empty
```

Its **output** is as follows −

```
Is the object empty?
False
```

ndim

Returns the number of dimensions of the object. By definition, DataFrame is a 2D object.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our object is:")
```

```
print df
print ("The dimension of the object is:")
print df.ndim
```

Its **output** is as follows −

```
Our object is:
      Age   Name    Rating
0     25    Tom      4.23
1     26    James    3.24
2     25    Ricky    3.98
3     23    Vin      2.56
4     30    Steve    3.20
5     29    Smith    4.60
6     23    Jack     3.80

The dimension of the object is:
2
```

shape

Returns a tuple representing the dimensionality of the DataFrame. Tuple (a,b), where a represents the number of rows and **b** represents the number of columns.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our object is:")
print df
```

```
print ("The shape of the object is:")
print df.shape
```

Its **output** is as follows −

```
Our object is:
    Age   Name    Rating
0  25    Tom     4.23
1  26    James   3.24
2  25    Ricky   3.98
3  23    Vin     2.56
4  30    Steve   3.20
5  29    Smith   4.60
6  23    Jack    3.80

The shape of the object is:
(7, 3)
```

size

Returns the number of elements in the DataFrame.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our object is:")
print df
print ("The total number of elements in our object is:")
print df.size
```

Its **output** is as follows −

```
Our object is:
    Age   Name    Rating
0   25    Tom     4.23
1   26    James   3.24
2   25    Ricky   3.98
3   23    Vin     2.56
4   30    Steve   3.20
5   29    Smith   4.60
6   23    Jack    3.80

The total number of elements in our object is:
21
```

values

Returns the actual data in the DataFrame as an **NDarray.**

[Live Demo]

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

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our object is:")
print df
print ("The actual data in our data frame is:")
print df.values
```

Its **output** is as follows −

Our object is:

```
   Age   Name    Rating
0   25    Tom     4.23
1   26    James   3.24
2   25    Ricky   3.98
3   23    Vin     2.56
4   30    Steve   3.20
5   29    Smith   4.60
6   23    Jack    3.80
The actual data in our data frame is:
[[25 'Tom' 4.23]
[26 'James' 3.24]
[25 'Ricky' 3.98]
[23 'Vin' 2.56]
[30 'Steve' 3.2]
[29 'Smith' 4.6]
[23 'Jack' 3.8]]
```

Head & Tail

To view a small sample of a DataFrame object, use the **head()** and tail() methods. **head()** returns the first **n** rows (observe the index values). The default number of elements to display is five, but you may pass a custom number.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our data frame is:")
print df
```

```
print ("The first two rows of the data frame is:")
print df.head(2)
```

Its **output** is as follows −

```
Our data frame is:
    Age   Name    Rating
0   25    Tom     4.23
1   26    James   3.24
2   25    Ricky   3.98
3   23    Vin     2.56
4   30    Steve   3.20
5   29    Smith   4.60
6   23    Jack    3.80

The first two rows of the data frame is:
   Age   Name   Rating
0  25    Tom    4.23
1  26    James  3.24
```

tail() returns the last **n** rows (observe the index values). The default number of elements to display is five, but you may pass a custom number.

Live Demo

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our data frame is:")
print df
print ("The last two rows of the data frame is:")
print df.tail(2)
```

Its **output** is as follows −

```
Our data frame is:
    Age   Name    Rating
0   25    Tom      4.23
1   26    James    3.24
2   25    Ricky    3.98
3   23    Vin      2.56
4   30    Steve    3.20
5   29    Smith    4.60
6   23    Jack     3.80

The last two rows of the data frame is:
    Age   Name    Rating
5   29    Smith     4.6
6   23    Jack      3.8
```

Chapter - 8 : Descriptive Statistics

A large number of methods collectively compute descriptive statistics and other related operations on DataFrame. Most of these are aggregations like **sum(), mean(),** but some of them, like **sumsum()**, produce an object of the same size. Generally speaking, these methods take an **axis** argument, just like ndarray.{sum, std, ...}, but the axis can be specified by name or integer

1. **DataFrame** − “index” (axis=0, default), “columns” (axis=1)

Let us create a DataFrame and use this object throughout this chapter for all the operations.

Example

Live Demo

```
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
```

Its **output** is as follows −

```
    Age  Name   Rating
0   25   Tom     4.23
1   26   James   3.24
2   25   Ricky   3.98
3   23   Vin     2.56
4   30   Steve   3.20
5   29   Smith   4.60
6   23   Jack    3.80
7   34   Lee     3.78
8   40   David   2.98
9   30   Gasper  4.80
10  51   Betina  4.10
11  46   Andres  3.65
```

sum()

Returns the sum of the values for the requested axis. By default, the axis is index (axis=0).

Live Demo

```
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.sum()
```

Its **output** is as follows −

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

Each individual column is added individually (Strings are appended).

axis=1

This syntax will give the output as shown below.

Live Demo

```
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.sum(1)
```

Its **output** is as follows −

```
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
```

mean()

Returns the average value

Live Demo

```
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.mean()
```

Its **output** is as follows −

```
Age      31.833333
Rating    3.743333
dtype: float64
```

std()

Returns the Bressel standard deviation of the numerical columns.

Live Demo

```
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.std()
```

Its **output** is as follows −

```
Age      9.232682
Rating   0.661628
dtype: float64
```

Functions & Description

Let us now understand the functions under Descriptive Statistics in Python Pandas. The following table list down the important functions −

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

Note − Since DataFrame is a Heterogeneous data structure. Generic operations don't work with all functions.

1. Functions like **sum(), cumsum()** work with both numeric and character (or) string data elements without any error. Though **in practice**, character aggregations are never used generally, these functions do not throw any exceptions.
2. Functions like **abs(), cumprod()** throw exceptions when the DataFrame contains character or string data because such operations cannot be performed.

Summarising Data

The **describe()** function computes a summary of statistics pertaining to the DataFrame columns.

Live Demo

```
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()
```

Its **output** is as follows −

```
               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
```

This function gives the **mean, std** and **IQR** values. And, function excludes the character columns and gives a summary about numeric columns. **'include'** is the argument which is used to pass necessary information regarding what columns need to be considered for summarising. Takes the list of values; by default, 'number'.

1. **object** − Summarizes String columns
2. **number** − Summarises Numeric columns
3. **all** − Summarises all columns together (Should not pass it as a list value)

Now, use the following statement in the program and check the output −

Live Demo

```
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(include=['object'])
```

Its **output** is as follows −

```
          Name
count       12
unique      12
top      Ricky
freq         1
```

Now, use the following statement and check the output −

Live Demo

```
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(include='all')
```

Its **output** is as follows −

```
          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
```

Chapter - 9 : Function Application

To apply your own or another library's functions to Pandas objects, you should be aware of the three important methods. The methods have been discussed below. The appropriate method to use depends on whether your function expects to operate on an entire DataFrame, row- or column-wise, or element wise.

1. Table wise Function Application: pipe()

2. Row or Column Wise Function Application: apply()
3. Element wise Function Application: applymap()

Table-wise Function Application

Custom operations can be performed by passing the function and the appropriate number of parameters as pipe arguments. Thus, operation is performed on the whole DataFrame.

For example, add a value 2 to all the elements in the DataFrame. Then,

adder function

The adder function adds two numeric values as parameters and returns the sum.

```
def adder(ele1,ele2):
   return ele1+ele2
```

We will now use the custom function to conduct operations on the DataFrame.

```
df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])
df.pipe(adder,2)
```

Let’s see the full program −

Live Demo

```
import pandas as pd
import numpy as np

def adder(ele1,ele2):
   return ele1+ele2

df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])
df.pipe(adder,2)
print df.apply(np.mean)
```

Its **output** is as follows −

```
      col1       col2       col3
0   2.176704   2.219691   1.509360
1   2.222378   2.422167   3.953921
2   2.241096   1.135424   2.696432
3   2.355763   0.376672   1.182570
4   2.308743   2.714767   2.130288
```

Row or Column Wise Function Application

Arbitrary functions can be applied along the axes of a DataFrame or Panel using the **apply()** method, which, like the descriptive statistics methods, takes an optional axis argument. By default, the operation performs column wise, taking each column as an array-like.

Example 1

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])
df.apply(np.mean)
print df.apply(np.mean)
```

Its **output** is as follows −

```
col1   -0.288022
col2    1.044839
col3   -0.187009
dtype: float64
```

By passing the axis parameter, operations can be performed row wise.

Example 2

Live Demo

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

```
df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])
df.apply(np.mean,axis=1)
print df.apply(np.mean)
```

Its **output** is as follows −

```
col1    0.034093
col2   -0.152672
col3   -0.229728
dtype: float64
```

Example 3

Live Demo

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

```
df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])
df.apply(lambda x: x.max() - x.min())
print df.apply(np.mean)
```

Its **output** is as follows −

```
col1   -0.167413
col2   -0.370495
col3   -0.707631
dtype: float64
```

Element Wise Function Application

Not all functions can be vectorized (neither the NumPy arrays which return another array nor any value), the methods **applymap()** on DataFrame and **analogously map()** on Series accept any Python function taking a single value and returning a single value.

Example 1

Live Demo

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

```
df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])

# My custom function
df['col1'].map(lambda x:x*100)
print df.apply(np.mean)
```

Its **output** is as follows −

```
col1    0.480742
col2    0.454185
col3    0.266563
dtype: float64
```

Example 2

[Live Demo]

```
import pandas as pd
import numpy as np

# My custom function
df = pd.DataFrame(np.random.randn(5,3),columns=['col1','col2','col3'])
df.applymap(lambda x:x*100)
print df.apply(np.mean)
```

Its **output** is as follows −

```
col1    0.395263
col2    0.204418
col3   -0.795188
dtype: float64
```

Chapter - 10 : Reindexing

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 −

1. Reorder the existing data to match a new set of labels.
2. Insert missing value (NA) markers in label locations where no data for the label existed.

Example

Live Demo

```
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()
})

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

print df_reindexed
```

Its **output** is as follows −

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

Reindex to Align with Other Objects

You may wish to take an object and reindex its axes to be labelled the same as another object. Consider the following example to understand the same.

Example

Live Demo

```
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
```

Its **output** is as follows −

```
        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
```

Note − Here, the **df1** DataFrame is altered and reindexed like **df2**. The column names should be matched or else NAN will be added for the entire column label.

Filling while ReIndexing

reindex() takes an optional parameter method which is a filling method with values as follows −

1. **pad/ffill** − Fill values forward
2. **bfill/backfill** − Fill values backward
3. **nearest** − Fill from the nearest index values

Example

Live Demo

```
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:")
print df2.reindex_like(df1,method='ffill')
```

Its **output** is as follows −

```
         col1        col2       col3
0    1.311620   -0.707176   0.599863
1   -0.423455   -0.700265   1.133371
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    1.311620   -0.707176    0.599863
1   -0.423455   -0.700265    1.133371
2   -0.423455   -0.700265    1.133371
3   -0.423455   -0.700265    1.133371
4   -0.423455   -0.700265    1.133371
5   -0.423455   -0.700265    1.133371
```

Note − The last four rows are padded.

Limits on Filling while Reindexing

The limit argument provides additional control over filling while reindexing. Limit specifies the maximum count of consecutive matches. Let us consider the following example to understand the same −

Example

Live Demo

```
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)
```

Its **output** is as follows −

```
         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
```

Note − Observe, only the 7th row is filled by the preceding 6th row. Then, the rows are left as they are.

Renaming

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

Let us consider the following example to understand this −

Live Demo

```
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'})
```

Its **output** is as follows −

```
         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
```

The rename() method provides an **inplace** named parameter, which by default is False and copies the underlying data. Pass **inplace=True** to rename the data in place.

Chapter - 11 : Iteration

The behaviour 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 −

1. **Series** − values
2. **DataFrame** − column labels
3. **Panel** − item labels

Iterating a DataFrame

Iterating a DataFrame gives column names. Let us consider the following example to understand the same.

Live Demo

```
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
```

Its **output** is as follows −

A
C
D
x
y

To iterate over the rows of the DataFrame, we can use the following functions −

1. **iteritems()** − to iterate over the (key,value) pairs
2. **iterrows()** − iterate over the rows as (index,series) pairs
3. **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.

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns=['col1','col2','col3'])
for key,value in df.iteritems():
   print key,value
```

Its **output** is as follows −

```
col1 0    0.802390
1    0.324060
2    0.256811
3    0.839186
Name: col1, dtype: float64

col2 0    1.624313
1   -1.033582
2    1.796663
3    1.856277
```

Name: col2, dtype: float64

```
col3 0   -0.022142
1   -0.230820
2    1.160691
3   -0.830279
Name: col3, dtype: float64
```

Observe, each column is iterated separately as a key-value pair in a Series.

iterrows()

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

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns = ['col1','col2','col3'])
for row_index,row in df.iterrows():
   print row_index,row
```

Its **output** is as follows −

```
0  col1    1.529759
   col2    0.762811
   col3   -0.634691
Name: 0, dtype: float64

1  col1   -0.944087
   col2    1.420919
   col3   -0.507895
Name: 1, dtype: float64

2  col1   -0.077287
   col2   -0.858556
   col3   -0.663385
Name: 2, dtype: float64
```

```
3  col1    -1.638578
   col2     0.059866
   col3     0.493482
Name: 3, dtype: float64
```

Note − Because **iterrows()** iterate over the rows, it doesn't preserve the data type across the row. 0,1,2 are the row indices and col1,col2,col3 are column indices.

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.

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(4,3),columns = ['col1','col2','col3'])
for row in df.itertuples():
   print row
```

Its **output** is as follows −

Pandas(Index=0, col1=1.5297586201375899, col2=0.76281127433814944, col3=-
0.6346908238310438)

Pandas(Index=1, col1=-0.94408735763808649,
col2=1.4209186418359423, col3=-
0.50789517967096232)

Pandas(Index=2, col1=-0.07728664756791935,
col2=-0.85855574139699076, col3=-
0.6633852507207626)

Pandas(Index=3, col1=0.65734942534106289,
col2=-0.95057710432604969,

col3=0.80344487462316527)

Note − Do not try to modify any object while iterating. Iterating is meant for reading and the iterator returns a copy of the original object (a view), thus the changes will not reflect on the original object.

Live Demo

```
import pandas as pd
import numpy as np

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

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

Its **output** is as follows −

```
        col1       col2       col3
0  -1.739815   0.735595  -0.295589
1   0.635485   0.106803   1.527922
2  -0.939064   0.547095   0.038585
3  -1.016509  -0.116580  -0.523158
```

Observe, no changes reflected.

Chapter - 12 : Sorting

There are two kinds of sorting available in Pandas. They are −

1. By label
2. By Actual Value

Let us consider an example with an output.

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

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

Its **output** is as follows −

```
        col2       col1
1  -2.063177   0.537527
4   0.142932  -0.684884
6   0.012667  -0.389340
2  -0.548797   1.848743
3  -1.044160   0.837381
5   0.385605   1.300185
9   1.031425  -1.002967
8  -0.407374  -0.435142
0   2.237453  -1.067139
7  -1.445831  -1.701035
```

In **unsorted_df**, the **labels** and the **values** are unsorted. Let us see how these can be sorted.

By Label

Using the **sort_index()** method, by passing the axis arguments and the order of sorting, DataFrame can be sorted. By default, sorting is done on row labels in ascending order.

```
import pandas as pd
import numpy as np

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

sorted_df=unsorted_df.sort_index()
print sorted_df
```

Its **output** is as follows −

```
      col2       col1
0   0.208464   0.627037
1   0.641004   0.331352
2  -0.038067  -0.464730
3  -0.638456  -0.021466
4   0.014646  -0.737438
5  -0.290761  -1.669827
6  -0.797303  -0.018737
7   0.525753   1.628921
8  -0.567031   0.775951
9   0.060724  -0.322425
```

Order of Sorting

By passing the Boolean value to the ascending parameter, the order of the sorting can be controlled. Let us consider the following example to understand the same.

```
import pandas as pd
import numpy as np

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

sorted_df = unsorted_df.sort_index(ascending=False)
print sorted_df
```

Its **output** is as follows −

```
       col2        col1
9    0.825697    0.374463
8   -1.699509    0.510373
7   -0.581378    0.622958
6   -0.202951    0.954300
5   -1.289321   -1.551250
4    1.302561    0.851385
3   -0.157915   -0.388659
```

```
2   -1.222295    0.166609
1    0.584890   -0.291048
0    0.668444   -0.061294
```

Sort the Columns

By passing the axis argument with a value 0 or 1, the sorting can be done on the column labels. By default, axis=0, sort by row. Let us consider the following example to understand the same.

```
import pandas as pd
import numpy as np

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

sorted_df=unsorted_df.sort_index(axis=1)
```

```
print sorted_df
```

Its **output** is as follows −

```
          col1        col2
1   -0.291048    0.584890
4    0.851385    1.302561
6    0.954300   -0.202951
2    0.166609   -1.222295
3   -0.388659   -0.157915
5   -1.551250   -1.289321
9    0.374463    0.825697
8    0.510373   -1.699509
0   -0.061294    0.668444
7    0.622958   -0.581378
```

By Value

Like index sorting, **sort_values()** is the method for sorting by values. It accepts a 'by' argument which will use the column name of the DataFrame with which the values are to be sorted.

```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame({'col1':[2,1,1,1],'col2':[1,3,2,4]})
   sorted_df = unsorted_df.sort_values(by='col1')

print sorted_df
```

Its **output** is as follows −

```
   col1  col2
1    1    3
2    1    2
3    1    4
0    2    1
```

Observe, col1 values are sorted and the respective col2 value and row index will alter along with col1. Thus, they look unsorted.

'by' argument takes a list of column values.

```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame({'col1':[2,1,1,1],'col2':[1,3,2,4]})
   sorted_df = unsorted_df.sort_values(by=['col1','col2'])

print sorted_df
```

Its **output** is as follows −

```
  col1 col2
2   1   2
1   1   3
3   1   4
0   2   1
```

Sorting Algorithm

sort_values() provides a provision to choose the algorithm from mergesort, heapsort and quicksort. Mergesort is the only stable algorithm.

Live Demo

```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame({'col1':[2,1,1,1],'col2':[1,3,2,4]})
sorted_df = unsorted_df.sort_values(by='col1' ,kind='mergesort')

print sorted_df
```

Its **output** is as follows −

```
 col1 col2
1    1    3
2    1    2
3    1    4
0    2    1
```

Chapter - 13 : Working with Text Data

In this chapter, we will discuss the string operations with our basic Series/Index. In the subsequent chapters, we will learn how to apply these string functions on the DataFrame.

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.

Almost, all of these methods work with Python string functions (refer: https://docs.python.org/3/library/stdtypes.html#string-methods). So, convert the Series Object to String Object and then perform the operation.

Let us now see how each operation performs.

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 a given separator.
7	**get_dummies()** Returns the DataFrame with One-Hot Encoded values.
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)** Repeat each element with a 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.

15 **findall(pattern)**
Returns a list of all occurrences 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.

Let us now create a Series and see how all the above functions work.

Live Demo
```
import pandas as pd
import numpy as np

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t', np.nan,
'1234','SteveSmith'])
```

```
print s
```

Its **output** is as follows −

```
0            Tom
1   William Rick
2           John
3        Alber@t
4            NaN
5           1234
6    Steve Smith
dtype: object
```

lower()

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t', np.nan,
'1234','SteveSmith'])

print s.str.lower()
```

Its **output** is as follows −

```
0            tom
1   william rick
2           john
3        alber@t
4            NaN
5           1234
6    steve smith
dtype: object
```

upper()

Live Demo

```
import pandas as pd
```

```
import numpy as np

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t', np.nan,
'1234','SteveSmith'])

print s.str.upper()
```

Its **output** is as follows −

```
0           TOM
1   WILLIAM RICK
2          JOHN
3       ALBER@T
4           NaN
5          1234
6    STEVE SMITH
dtype: object
```

len()

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t', np.nan,
'1234','SteveSmith'])
print s.str.len()
```

Its **output** is as follows −

```
0    3.0
1   12.0
2    4.0
3    7.0
4    NaN
5    4.0
6   10.0
dtype: float64
```

strip()

Live Demo

```
import pandas as pd
import numpy as np
s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])
print s
print ("After Stripping:")
print s.str.strip()
```

Its **output** is as follows −

```
0           Tom
1   William Rick
2          John
3       Alber@t
dtype: object

After Stripping:
0           Tom
1   William Rick
2          John
3       Alber@t
dtype: object
```

split(pattern)

Live Demo

```
import pandas as pd
import numpy as np
s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])
print s
print ("Split Pattern:")
print s.str.split(' ')
```

Its **output** is as follows −

```
0           Tom
1   William Rick
```

```
2          John
3       Alber@t
dtype: object
```

```
Split Pattern:
0   [Tom, , , , , , , , , , ]
1   [, , , , , William, Rick]
2   [John]
3   [Alber@t]
dtype: object
```

cat(sep=pattern)

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print s.str.cat(sep='_')
```

Its **output** is as follows −

```
Tom _ William Rick_John_Alber@t
```

get_dummies()

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print s.str.get_dummies()
```

Its **output** is as follows −

```
   William Rick   Alber@t   John   Tom
0             0         0      0     1
1             1         0      0     0
2             0         0      1     0
```

3   0   1   0   0

contains ()

Live Demo

```
import pandas as pd

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print s.str.contains(' ')
```

Its **output** is as follows −

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

replace(a,b)

Live Demo

```
import pandas as pd
s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])
print s
print ("After replacing @ with $:")
print s.str.replace('@','$')
```

Its **output** is as follows −

```
0   Tom
1   William Rick
2   John
3   Alber@t
dtype: object

After replacing @ with $:
0   Tom
1   William Rick
2   John
```

3   Albert
dtype: object

repeat(value)

Live Demo

```
import pandas as pd

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print s.str.repeat(2)
```

Its **output** is as follows −

```
0   Tom          Tom
1   William Rick   William Rick
2                  JohnJohn
3                  Alber@tAlber@t
dtype: object
```

count(pattern)

Live Demo

```
import pandas as pd

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print ("The number of 'm's in each string:")
print s.str.count('m')
```

Its **output** is as follows −

```
The number of 'm's in each string:
0    1
1    1
2    0
3    0
```

startswith(pattern)

Live Demo

```
import pandas as pd

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print ("Strings that start with 'T':")
print s.str. startswith ('T')
```

Its **output** is as follows −

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

endswith(pattern)

Live Demo

```
import pandas as pd
s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])
print ("Strings that end with 't':")
print s.str.endswith('t')
```

Its **output** is as follows −

```
Strings that end with 't':
0  False
1  False
2  False
3  True
dtype: bool
```

find(pattern)

Live Demo

```
import pandas as pd

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])
```

```
print s.str.find('e')
```

Its **output** is as follows −

```
0  -1
1  -1
2  -1
3   3
dtype: int64
```

"-1" indicates that there is no such pattern available in the element.

findall(pattern)

Live Demo

```
import pandas as pd

s = pd.Series(['Tom ', ' William Rick', 'John', 'Alber@t'])

print s.str.findall('e')
```

Its **output** is as follows −

```
0 []
1 []
2 []
3 [e]
dtype: object
```

Null list([ ]) indicates that there is no such pattern available in the element.

swapcase()

Live Demo

```
import pandas as pd

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t'])
print s.str.swapcase()
```

Its **output** is as follows −

```
0  tOM
```

```
1  wILLIAM rICK
2  jOHN
3  aLBER@T
dtype: object
```

islower()

Live Demo

```python
import pandas as pd

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t'])
print s.str.islower()
```

Its **output** is as follows −

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

isupper()

Live Demo

```python
import pandas as pd

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t'])

print s.str.isupper()
```

Its **output** is as follows −

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

isnumeric()

Live Demo

```
import pandas as pd

s = pd.Series(['Tom', 'William Rick', 'John', 'Alber@t'])

print s.str.isnumeric()
```

Its **output** is as follows −

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

Chapter - 14 : Options and Customization

Pandas provide API to customise some aspects of its behaviour, display is being mostly used.

The API is composed of five relevant functions. They are −

1. get_option()
2. set_option()
3. reset_option()
4. describe_option()
5. option_context()

Let us now understand how the functions operate.

get_option(param)

get_option takes a single parameter and returns the value as given in the output below −

display.max_rows

Displays the default number of values. Interpreter reads this value and displays the rows with this value as upper limit to display.

Live Demo
```
import pandas as pd
print pd.get_option("display.max_rows")
```

Its **output** is as follows −

```
60
```

display.max_columns

Displays the default number of values. Interpreter reads this value and displays the rows with this value as upper limit to display.

Live Demo
```
import pandas as pd
print pd.get_option("display.max_columns")
```

Its **output** is as follows −

```
20
```

Here, 60 and 20 are the default configuration parameter values.

set_option(param,value)

set_option takes two arguments and sets the value to the parameter as shown below −

display.max_rows

Using **set_option()**, we can change the default number of rows to be displayed.

Live Demo
```
import pandas as pd

pd.set_option("display.max_rows",80)
```

```
print pd.get_option("display.max_rows")
```

Its **output** is as follows −

80

display.max_columns

Using **set_option()**, we can change the default number of rows to be displayed.

Live Demo

```
import pandas as pd

pd.set_option("display.max_columns",30)

print pd.get_option("display.max_columns")
```

Its **output** is as follows −

30

reset_option(param)

reset_option takes an argument and sets the value back to the default value.

display.max_rows

Using reset_option(), we can change the value back to the default number of rows to be displayed.

Live Demo

```
import pandas as pd

pd.reset_option("display.max_rows")
print pd.get_option("display.max_rows")
```

Its **output** is as follows −

60

describe_option(param)

describe_option prints the description of the argument.

display.max_rows

Using reset_option(), we can change the value back to the default number of rows to be displayed.

Live Demo

```
import pandas as pd
pd.describe_option("display.max_rows")
```

Its **output** is as follows −

```
display.max_rows : int
   If max_rows is exceeded, switch to truncate view. Depending on
   'large_repr', objects are either centrally truncated or printed as
   a summary view. 'None' value means unlimited.

   In case python/IPython is running in a terminal and `large_repr`
   equals 'truncate' this can be set to 0 and pandas will auto-detect
   the height of the terminal and print a truncated object which fits
   the screen height. The IPython notebook, IPython qtconsole, or
   IDLE do not run in a terminal and hence it is not possible to do
   correct auto-detection.
   [default: 60] [currently: 60]
```

option_context()

option_context context manager is used to set the option in **with a statement** temporarily. Option values are restored automatically when you exit the **with block** −

display.max_rows

Using option_context(), we can set the value temporarily.

Live Demo

```
import pandas as pd
with pd.option_context("display.max_rows",10):
   print(pd.get_option("display.max_rows"))
   print(pd.get_option("display.max_rows"))
```

Its **output** is as follows −

```
10
10
```

See, the difference between the first and the second print statements. The first statement prints the value set by **option_context()** which is temporary within the context itself. After the **with context**, the second print statement prints the configured value.

Frequently used Parameters

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

Chapter - 15 : Indexing and Selecting Data

In this chapter, we will discuss how to slice and dice the date and generally get the subset of pandas objects.

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 optimised pandas data access methods explained in this chapter.

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 −

1. A single scalar label

2. A list of labels
3. A slice object
4. A Boolean array

loc takes two single/list/range operators separated by ','. The first one indicates the row and the second one indicates columns.

Example 1

[Live Demo]

```
#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'])

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

Its **output** is as follows −

```
a   0.391548
b  -0.070649
c  -0.317212
d  -2.162406
e   2.202797
f   0.613709
g   1.050559
h   1.122680
Name: A, dtype: float64
```

Example 2

[Live Demo]

```
# 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'])

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

Its **output** is as follows −

```
          A         C
a  0.391548  0.745623
b -0.070649  1.620406
c -0.317212  1.448365
d -2.162406 -0.873557
e  2.202797  0.528067
f  0.613709  0.286414
g  1.050559  0.216526
h  1.122680 -1.621420
```

Example 3

Live Demo

```
# 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'])

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

Its **output** is as follows −

```
          A         C
a  0.391548  0.745623
b -0.070649  1.620406
f  0.613709  0.286414
h  1.122680 -1.621420
```

Example 4

Live Demo

```
# 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'])

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

Its **output** is as follows −

```
        A           B          C          D
a   0.391548   -0.224297   0.745623   0.054301
b  -0.070649   -0.880130   1.620406   1.419743
c  -0.317212   -1.929698   1.448365   0.616899
d  -2.162406    0.614256  -0.873557   1.093958
e   2.202797   -2.315915   0.528067   0.612482
f   0.613709   -0.157674   0.286414  -0.500517
g   1.050559   -2.272099   0.216526   0.928449
h   1.122680    0.324368  -1.621420  -0.741470
```

Example 5

Live Demo

```
# 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'])

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

Its **output** is as follows −

```
A  False
B  True
C  False
D  False
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 −

1. An Integer
2. A list of integers
3. A range of values

Example 1

Live Demo

```
# 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'])

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

Its **output** is as follows −

```
          A          B          C          D
0   0.699435   0.256239  -1.270702  -0.645195
1  -0.685354   0.890791  -0.813012   0.631615
2  -0.783192  -0.531378   0.025070   0.230806
3   0.539042  -1.284314   0.826977  -0.026251
```

Example 2

Live Demo

```
import pandas as pd
import numpy as np

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

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

Its **output** is as follows −

```
          A          B          C          D
0   0.699435   0.256239  -1.270702  -0.645195
1  -0.685354   0.890791  -0.813012   0.631615
2  -0.783192  -0.531378   0.025070   0.230806
3   0.539042  -1.284314   0.826977  -0.026251

           C          D
1  -0.813012   0.631615
2   0.025070   0.230806
3   0.826977  -0.026251
4   1.423332   1.130568
```

Example 3

Live Demo

```
import pandas as pd
import numpy as np

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

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

Its **output** is as follows −

```
          B          D
1   0.890791   0.631615
```

```
3  -1.284314   -0.026251
5  -0.512888   -0.518930
```

```
          A          B          C          D
1  -0.685354   0.890791  -0.813012   0.631615
2  -0.783192  -0.531378   0.025070   0.230806
```

```
          B          C
0   0.256239  -1.270702
1   0.890791  -0.813012
2  -0.531378   0.025070
3  -1.284314   0.826977
4  -0.460729   1.423332
5  -0.512888   0.581409
6  -1.204853   0.098060
7  -0.947857   0.641358
```

.ix()

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

Example 1

Live Demo

```
import pandas as pd
import numpy as np

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

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

Its **output** is as follows −

```
          A          B          C          D
0   0.699435   0.256239  -1.270702  -0.645195
1  -0.685354   0.890791  -0.813012   0.631615
2  -0.783192  -0.531378   0.025070   0.230806
```

3   0.539042 -1.284314   0.826977   -0.026251

Example 2

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(8, 4), columns = ['A', 'B', 'C', 'D'])
# Index slicing
print df.ix[:,'A']
```

Its **output** is as follows −

```
0   0.699435
1  -0.685354
2  -0.783192
3   0.539042
4  -1.044209
5  -1.415411
6   1.062095
7   0.994204
Name: A, dtype: float64
```

Use of Notations

Getting values from the Pandas object with Multi-axes indexing uses the following notation −

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]

Note − .iloc() & .ix() applies the same indexing options and Return value.

Let us now see how each operation can be performed on the DataFrame object. We will use the basic indexing operator '[ ]' −

Example 1

Live Demo

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

Its **output** is as follows −

```
0  -0.478893
1   0.391931
2   0.336825
3  -1.055102
4  -0.165218
5  -0.328641
6   0.567721
7  -0.759399
Name: A, dtype: float64
```

Note − We can pass a list of values to [ ] to select those columns.

Example 2

Live Demo

```
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']]
```

Its **output** is as follows −

```
          A           B
0  -0.478893   -0.606311
```

```
1   0.391931   -0.949025
2   0.336825    0.093717
3  -1.055102   -0.012944
4  -0.165218    1.550310
5  -0.328641   -0.226363
6   0.567721   -0.312585
7  -0.759399   -0.372696
```

Example 3

Live Demo

```
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(8, 4), columns = ['A', 'B', 'C', 'D'])
print df[2:2]
```

Its **output** is as follows −

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

Attribute Access

Columns can be selected using the attribute operator '.'.

Example

Live Demo

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

print df.A
```

Its **output** is as follows −

```
0   -0.478893
1    0.391931
2    0.336825
3   -1.055102
```

```
4   -0.165218
5   -0.328641
6    0.567721
7   -0.759399
Name: A, dtype: float64
```

Chapter - 16 : Statistical Functions

Statistical methods help in the understanding and analysing the behaviour of data. We will now learn a few statistical functions, which we can apply on Pandas objects.

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.

Live Demo

```
import pandas as pd
import numpy as np
s = pd.Series([1,2,3,4,5,4])
print s.pct_change()

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

Its **output** is as follows −

```
0        NaN
1   1.000000
2   0.500000
3   0.333333
4   0.250000
```

```
5  -0.200000
dtype: float64
```

```
           0         1
0        NaN       NaN
1 -15.151902  0.174730
2  -0.746374 -1.449088
3  -3.582229 -3.165836
4  15.601150 -1.860434
```

By default, the **pct_change()** operates on columns; if you want to apply the same row wise, then use the axis**=1()** argument.

Covariance

Covariance is applied on series data. The Series object has a method cov to compute covariance between series objects. NA will be excluded automatically.

Cov Series

Live Demo

```
import pandas as pd
import numpy as np
s1 = pd.Series(np.random.randn(10))
s2 = pd.Series(np.random.randn(10))
print s1.cov(s2)
```

Its **output** is as follows −

```
-0.12978405324
```

Covariance method when applied on a DataFrame, computes **cov** between all the columns.

Live Demo

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

```
print frame['a'].cov(frame['b'])
print frame.cov()
```

Its **output** is as follows −

```
-0.58312921152741437

           a          b          c          d          e
a   1.780628  -0.583129  -0.185575   0.003679  -0.136558
b  -0.583129   1.297011   0.136530  -0.523719   0.251064
c  -0.185575   0.136530   0.915227  -0.053881  -0.058926
d   0.003679  -0.523719  -0.053881   1.521426  -0.487694
e  -0.136558   0.251064  -0.058926  -0.487694   0.960761
```

Note − Observe the **cov** between **a** and **b** column in the first statement and the same is the value returned by cov on DataFrame.

Correlation

Correlation shows the linear relationship between any two arrays of values (series). There are multiple methods to compute the correlation like pearson(default), spearman and kendall.

Live Demo

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

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

Its **output** is as follows −

```
-0.383712785514

           a          b          c          d          e
a   1.000000  -0.383713  -0.145368   0.002235  -0.104405
b  -0.383713   1.000000   0.125311  -0.372821   0.224908
c  -0.145368   0.125311   1.000000  -0.045661  -0.062840
d   0.002235  -0.372821  -0.045661   1.000000  -0.403380
```

e -0.104405   0.224908 -0.062840 -0.403380   1.000000

If any non-numeric column is present in the DataFrame, it is excluded automatically.

Data Ranking

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

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Series(np.random.np.random.randn(5), index=list('abcde'))
s['d'] = s['b'] # so there's a tie
print s.rank()
```

Its **output** is as follows −

```
a  1.0
b  3.5
c  2.0
d  3.5
e  5.0
dtype: float64
```

Rank optionally takes a parameter ascending which by default is true; when false, data is reverse-ranked, with larger values assigned a smaller rank.

Rank supports different tie-breaking methods, specified with the method parameter −

1. **average** − average rank of tied group
2. **min** − lowest rank in the group
3. **max** − highest rank in the group
4. **first** − ranks assigned in the order they appear in the array

Chapter - 17 : Window Functions

For working on numerical data, Pandas provide few variants like rolling, expanding and exponentially moving weights for window statistics. Among these are **sum, mean, median, variance, covariance, correlation,** etc.

We will now learn how each of these can be applied on DataFrame objects.

.rolling() Function

This function can be applied on a series of data. Specify the **window=n** argument and apply the appropriate statistical function on top of it.

Live Demo

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

Its **output** is as follows −

```
                A          B          C          D
2000-01-01       NaN        NaN        NaN        NaN
2000-01-02       NaN        NaN        NaN        NaN
2000-01-03  0.434553  -0.667940  -1.051718  -0.826452
2000-01-04  0.628267  -0.047040  -0.287467  -0.161110
2000-01-05  0.398233   0.003517   0.099126  -0.405565
2000-01-06  0.641798   0.656184  -0.322728   0.428015
2000-01-07  0.188403   0.010913  -0.708645   0.160932
2000-01-08  0.188043  -0.253039  -0.818125  -0.108485
2000-01-09  0.682819  -0.606846  -0.178411  -0.404127
2000-01-10  0.688583   0.127786   0.513832  -1.067156
```

Note − Since the window size is 3, for the first two elements there are nulls and from the third the value will be the average of the **n**, **n-1** and **n-2** elements. Thus we can also apply various functions as mentioned above.

.expanding() Function

This function can be applied on a series of data. Specify the **min_periods=n** argument and apply the appropriate statistical function on top of it.

Live Demo

```
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.expanding(min_periods=3).mean()
```

Its **output** is as follows −

```
                   A           B           C           D
2000-01-01        NaN         NaN         NaN         NaN
2000-01-02        NaN         NaN         NaN         NaN
2000-01-03   0.434553   -0.667940   -1.051718   -0.826452
2000-01-04   0.743328   -0.198015   -0.852462   -0.262547
2000-01-05   0.614776   -0.205649   -0.583641   -0.303254
2000-01-06   0.538175   -0.005878   -0.687223   -0.199219
2000-01-07   0.505503   -0.108475   -0.790826   -0.081056
2000-01-08   0.454751   -0.223420   -0.671572   -0.230215
2000-01-09   0.586390   -0.206201   -0.517619   -0.267521
2000-01-10   0.560427   -0.037597   -0.399429   -0.376886
```

.ewm() Function

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.

[Live Demo]

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

Its **output** is as follows −

```
                   A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   0.865131   -0.453626   -1.137961    0.058747
2000-01-03  -0.132245   -0.807671   -0.308308   -1.491002
2000-01-04   1.084036    0.555444   -0.272119    0.480111
2000-01-05   0.425682    0.025511    0.239162   -0.153290
2000-01-06   0.245094    0.671373   -0.725025    0.163310
2000-01-07   0.288030   -0.259337   -1.183515    0.473191
2000-01-08   0.162317   -0.771884   -0.285564   -0.692001
2000-01-09   1.147156   -0.302900    0.380851   -0.607976
2000-01-10   0.600216    0.885614    0.569808   -1.110113
```

Window functions are majorly used in finding the trends within the data graphically by smoothing the curve. If there is a lot of variation in the everyday data and a lot of data points are available, then taking the samples and plotting is one method and applying the window computations and plotting the graph on the results is another method. By these methods, we can smooth the curve or the trend.

Chapter - 18 : Aggregations

Once the rolling, expanding and **ewm** objects are created, several methods are available to perform aggregations on data.

Applying Aggregations on DataFrame

Let us create a DataFrame and apply aggregations on it.

Live Demo

```
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
r = df.rolling(window=3,min_periods=1)
print r
```

Its **output** is as follows −

```
                 A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   0.790670   -0.387854   -0.668132    0.267283
2000-01-03  -0.575523   -0.965025    0.060427   -2.179780
2000-01-04   1.669653    1.211759   -0.254695    1.429166
2000-01-05   0.100568   -0.236184    0.491646   -0.466081
2000-01-06   0.155172    0.992975   -1.205134    0.320958
2000-01-07   0.309468   -0.724053   -1.412446    0.627919
2000-01-08   0.099489   -1.028040    0.163206   -1.274331
2000-01-09   1.639500   -0.068443    0.714008   -0.565969
2000-01-10   0.326761    1.479841    0.664282   -1.361169

Rolling [window=3,min_periods=1,centre=False,axis=0]
```

We can aggregate by passing a function to the entire DataFrame, or select a column via the standard **get item** method.

Apply Aggregation on a Whole Dataframe

Live Demo

```
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
r = df.rolling(window=3,min_periods=1)
print r.aggregate(np.sum)
```

Its **output** is as follows −

```
                 A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   1.879182   -1.038796   -3.215581   -0.299575
2000-01-03   1.303660   -2.003821   -3.155154   -2.479355
2000-01-04   1.884801   -0.141119   -0.862400   -0.483331
2000-01-05   1.194699    0.010551    0.297378   -1.216695
2000-01-06   1.925393    1.968551   -0.968183    1.284044
2000-01-07   0.565208    0.032738   -2.125934    0.482797
2000-01-08   0.564129   -0.759118   -2.454374   -0.325454
2000-01-09   2.048458   -1.820537   -0.535232   -1.212381
2000-01-10   2.065750    0.383357    1.541496   -3.201469

                 A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   1.879182   -1.038796   -3.215581   -0.299575
2000-01-03   1.303660   -2.003821   -3.155154   -2.479355
2000-01-04   1.884801   -0.141119   -0.862400   -0.483331
2000-01-05   1.194699    0.010551    0.297378   -1.216695
2000-01-06   1.925393    1.968551   -0.968183    1.284044
2000-01-07   0.565208    0.032738   -2.125934    0.482797
2000-01-08   0.564129   -0.759118   -2.454374   -0.325454
2000-01-09   2.048458   -1.820537   -0.535232   -1.212381
2000-01-10   2.065750    0.383357    1.541496   -3.201469
```

Apply Aggregation on a Single Column of a Dataframe

Live Demo

```
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
r = df.rolling(window=3,min_periods=1)
print r['A'].aggregate(np.sum)
```

Its **output** is as follows −

```
                 A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   1.879182   -1.038796   -3.215581   -0.299575
2000-01-03   1.303660   -2.003821   -3.155154   -2.479355
2000-01-04   1.884801   -0.141119   -0.862400   -0.483331
2000-01-05   1.194699    0.010551    0.297378   -1.216695
2000-01-06   1.925393    1.968551   -0.968183    1.284044
2000-01-07   0.565208    0.032738   -2.125934    0.482797
2000-01-08   0.564129   -0.759118   -2.454374   -0.325454
2000-01-09   2.048458   -1.820537   -0.535232   -1.212381
2000-01-10   2.065750    0.383357    1.541496   -3.201469
2000-01-01   1.088512
2000-01-02   1.879182
2000-01-03   1.303660
2000-01-04   1.884801
2000-01-05   1.194699
2000-01-06   1.925393
2000-01-07   0.565208
2000-01-08   0.564129
2000-01-09   2.048458
2000-01-10   2.065750
Freq: D, Name: A, dtype: float64
```

Apply Aggregation on Multiple Columns of a DataFrame

Live Demo

```
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
r = df.rolling(window=3,min_periods=1)
print r[['A','B']].aggregate(np.sum)
```

Its **output** is as follows −

```
                 A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   1.879182   -1.038796   -3.215581   -0.299575
2000-01-03   1.303660   -2.003821   -3.155154   -2.479355
2000-01-04   1.884801   -0.141119   -0.862400   -0.483331
2000-01-05   1.194699    0.010551    0.297378   -1.216695
2000-01-06   1.925393    1.968551   -0.968183    1.284044
2000-01-07   0.565208    0.032738   -2.125934    0.482797
2000-01-08   0.564129   -0.759118   -2.454374   -0.325454
2000-01-09   2.048458   -1.820537   -0.535232   -1.212381
2000-01-10   2.065750    0.383357    1.541496   -3.201469
                    A           B
2000-01-01   1.088512   -0.650942
2000-01-02   1.879182   -1.038796
2000-01-03   1.303660   -2.003821
2000-01-04   1.884801   -0.141119
2000-01-05   1.194699    0.010551
2000-01-06   1.925393    1.968551
2000-01-07   0.565208    0.032738
2000-01-08   0.564129   -0.759118
2000-01-09   2.048458   -1.820537
2000-01-10   2.065750    0.383357
```

Apply Multiple Functions on a Single Column of a DataFrame

Live Demo

```
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
r = df.rolling(window=3,min_periods=1)
print r['A'].aggregate([np.sum,np.mean])
```

Its **output** is as follows −

```
                 A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   1.879182   -1.038796   -3.215581   -0.299575
2000-01-03   1.303660   -2.003821   -3.155154   -2.479355
2000-01-04   1.884801   -0.141119   -0.862400   -0.483331
2000-01-05   1.194699    0.010551    0.297378   -1.216695
2000-01-06   1.925393    1.968551   -0.968183    1.284044
2000-01-07   0.565208    0.032738   -2.125934    0.482797
2000-01-08   0.564129   -0.759118   -2.454374   -0.325454
2000-01-09   2.048458   -1.820537   -0.535232   -1.212381
2000-01-10   2.065750    0.383357    1.541496   -3.201469
                  sum       mean
2000-01-01   1.088512   1.088512
2000-01-02   1.879182   0.939591
2000-01-03   1.303660   0.434553
2000-01-04   1.884801   0.628267
2000-01-05   1.194699   0.398233
2000-01-06   1.925393   0.641798
2000-01-07   0.565208   0.188403
2000-01-08   0.564129   0.188043
2000-01-09   2.048458   0.682819
```

```
2000-01-10   2.065750   0.688583
```

Apply Multiple Functions on Multiple Columns of a DataFrame

Live Demo

```
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
r = df.rolling(window=3,min_periods=1)
print r[['A','B']].aggregate([np.sum,np.mean])
```

Its **output** is as follows −

```
                    A           B           C           D
2000-01-01   1.088512   -0.650942   -2.547450   -0.566858
2000-01-02   1.879182   -1.038796   -3.215581   -0.299575
2000-01-03   1.303660   -2.003821   -3.155154   -2.479355
2000-01-04   1.884801   -0.141119   -0.862400   -0.483331
2000-01-05   1.194699    0.010551    0.297378   -1.216695
2000-01-06   1.925393    1.968551   -0.968183    1.284044
2000-01-07   0.565208    0.032738   -2.125934    0.482797
2000-01-08   0.564129   -0.759118   -2.454374   -0.325454
2000-01-09   2.048458   -1.820537   -0.535232   -1.212381
2000-01-10   2.065750    0.383357    1.541496   -3.201469
                    A                      B
                  sum       mean         sum        mean
2000-01-01   1.088512   1.088512   -0.650942   -0.650942
2000-01-02   1.879182   0.939591   -1.038796   -0.519398
2000-01-03   1.303660   0.434553   -2.003821   -0.667940
2000-01-04   1.884801   0.628267   -0.141119   -0.047040
2000-01-05   1.194699   0.398233    0.010551    0.003517
2000-01-06   1.925393   0.641798    1.968551    0.656184
```

```
2000-01-07   0.565208   0.188403    0.032738    0.010913
2000-01-08   0.564129   0.188043   -0.759118   -0.253039
2000-01-09   2.048458   0.682819   -1.820537   -0.606846
2000-01-10   2.065750   0.688583    0.383357    0.127786
```

Apply Different Functions to Different Columns of a Dataframe

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(3, 4),
   index = pd.date_range('1/1/2000', periods=3),
   columns = ['A', 'B', 'C', 'D'])
print df
r = df.rolling(window=3,min_periods=1)
print r.aggregate({'A' : np.sum,'B' : np.mean})
```

Its **output** is as follows −

```
                    A           B           C          D
2000-01-01  -1.575749  -1.018105   0.317797  0.545081
2000-01-02  -0.164917  -1.361068   0.258240  1.113091
2000-01-03   1.258111   1.037941  -0.047487  0.867371
                    A           B
2000-01-01  -1.575749  -1.018105
2000-01-02  -1.740666  -1.189587
2000-01-03  -0.482555  -0.447078
```

Chapter - 19 : Missing Data

Missing data is always a problem in real life scenarios. Areas like machine learning and data mining face severe issues in the accuracy of their model predictions because of poor quality of data caused by missing values. In these areas, missing value treatment is a major point of focus to make their models more accurate and valid.

When and Why Is Data Missed?

Let us consider an online survey for a product. Many times, people do not share all the information related to them. Few people share their experience, but not how long they are using the product; few people share how long they are using the product, their experience but not their contact information. Thus, in some or the other way a part of data is always missing, and this is very common in real time.

Let us now see how we can handle missing values (say NA or NaN) using Pandas.

[Live Demo]

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

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print df
```

Its **output** is as follows −

```
        one        two      three
a   0.077988   0.476149   0.965836
b        NaN        NaN        NaN
c  -0.390208  -0.551605  -2.301950
d        NaN        NaN        NaN
e  -2.000303  -0.788201   1.510072
f  -0.930230  -0.670473   1.146615
```

```
g        NaN        NaN        NaN
h   0.085100   0.532791   0.887415
```

Using reindexing, we have created a DataFrame with missing values. In the output, **NaN** means **Not a Number.**

Check for Missing Values

To make detecting missing values easier (and across different array dtypes), Pandas provides the **isnull()** and **notnull()** functions, which are also methods on Series and DataFrame objects −

Example 1

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print df['one'].isnull()
```

Its **output** is as follows −

```
a  False
b  True
c  False
d  True
e  False
f  False
g  True
h  False
Name: one, dtype: bool
```

Example 2

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print df['one'].notnull()
```

Its **output** is as follows −

```
a  True
b  False
c  True
d  False
e  True
f  True
g  False
h  True
Name: one, dtype: bool
```

Calculations with Missing Data

- When summing data, NA will be treated as Zero
- If the data are all NA, then the result will be NA

Example 1

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print df['one'].sum()
```

Its **output** is as follows −

2.02357685917

Example 2

[Live Demo]

```
import pandas as pd
import numpy as np

df = pd.DataFrame(index=[0,1,2,3,4,5],columns=['one','two'])
print df['one'].sum()
```

Its **output** is as follows −

nan

Cleaning / Filling Missing Data

Pandas provides various methods for cleaning the missing values. The fillna function can “fill in” NA values with non-null data in a couple of ways, which we have illustrated in the following sections.

Replace NaN with a Scalar Value

The following program shows how you can replace "NaN" with "0".

[Live Demo]

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(3, 3), index=['a', 'c', 'e'],columns=
['one',
'two', 'three'])

df = df.reindex(['a', 'b', 'c'])

print df
print ("NaN replaced with '0':")
print df.fillna(0)
```

Its **output** is as follows −

```
        one        two     three
a  -0.576991  -0.741695  0.553172
b        NaN        NaN       NaN
c   0.744328  -1.735166  1.749580
```

```
NaN replaced with '0':
         one        two     three
a  -0.576991  -0.741695  0.553172
b   0.000000   0.000000  0.000000
c   0.744328  -1.735166  1.749580
```

Here, we are filling with value zero; instead we can also fill with any other value.

Fill NA Forward and Backward

Using the concepts of filling discussed in the ReIndexing Chapter we will fill the missing values.

Sr.No	Method & Action
1	**pad/fill** Fill methods Forward
2	**bfill/backfill** Fill methods Backward

Example 1

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
```

```
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print df.fillna(method='pad')
```

Its **output** is as follows −

```
        one        two      three
a   0.077988   0.476149   0.965836
b   0.077988   0.476149   0.965836
c  -0.390208  -0.551605  -2.301950
d  -0.390208  -0.551605  -2.301950
e  -2.000303  -0.788201   1.510072
f  -0.930230  -0.670473   1.146615
g  -0.930230  -0.670473   1.146615
h   0.085100   0.532791   0.887415
```

Example 2

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print df.fillna(method='backfill')
```

Its **output** is as follows −

```
        one        two      three
a   0.077988   0.476149   0.965836
b  -0.390208  -0.551605  -2.301950
c  -0.390208  -0.551605  -2.301950
d  -2.000303  -0.788201   1.510072
e  -2.000303  -0.788201   1.510072
f  -0.930230  -0.670473   1.146615
```

```
g   0.085100   0.532791   0.887415
h   0.085100   0.532791   0.887415
```

Drop Missing Values

If you want to simply exclude the missing values, then use the **dropna** function along with the **axis** argument. By default, axis=0, i.e., a long row, which means that if any value within a row is NA then the whole row is excluded.

Example 1

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print df.dropna()
```

Its **output** is as follows −

```
        one        two      three
a   0.077988   0.476149   0.965836
c  -0.390208  -0.551605  -2.301950
e  -2.000303  -0.788201   1.510072
f  -0.930230  -0.670473   1.146615
h   0.085100   0.532791   0.887415
```

Example 2

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])
```

```
df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print df.dropna(axis=1)
```

Its **output** is as follows −

```
Empty DataFrame
Columns: [ ]
Index: [a, b, c, d, e, f, g, h]
```

Replace Missing (or) Generic Values

Many times, we have to replace a generic value with some specific value. We can achieve this by applying the replace method.

Replacing NA with a scalar value is equivalent behaviour of the **fillna()** function.

Example 1

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame({'one':[10,20,30,40,50,2000], 'two':
[1000,0,30,40,50,60]})

print df.replace({1000:10,2000:60})
```

Its **output** is as follows −

```
   one  two
0   10   10
1   20    0
2   30   30
3   40   40
4   50   50
5   60   60
```

Example 2

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame({'one':[10,20,30,40,50,2000], 'two':
[1000,0,30,40,50,60]})
print df.replace({1000:10,2000:60})
```

Its **output** is as follows −

```
   one  two
0   10   10
1   20    0
2   30   30
3   40   40
4   50   50
5   60   60
```

Chapter - 20 : GroupBy

Any **groupby** operation involves one of the following operations on the original object. They are −

1. **Splitting** the Object
2. **Applying** a function
3. **Combining** the results

In many situations, we split the data into sets and we apply some functionality on each subset. In the apply functionality, we can perform the following operations −

1. **Aggregation** − computing a summary statistic
2. **Transformation** − perform some group-specific operation
3. **Filtration** − discarding the data with some condition

Let us now create a DataFrame object and perform all the operations on it −

Live Demo

```
#import the pandas library
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

print df
```

Its **output** is as follows −

```
    Points   Rank     Team   Year
0      876      1   Riders   2014
1      789      2   Riders   2015
2      863      2   Devils   2014
3      673      3   Devils   2015
4      741      3    Kings   2014
5      812      4    kings   2015
6      756      1    Kings   2016
7      788      1    Kings   2017
8      694      2   Riders   2016
9      701      4   Royals   2014
10     804      1   Royals   2015
11     690      2   Riders   2017
```

Split Data into Groups

Pandas objects can be split into any of their objects. There are multiple ways to split an object like −

- obj.groupby('key')

- obj.groupby(['key1','key2'])
- obj.groupby(key,axis=1)

Let us now see how the grouping objects can be applied to the DataFrame object

Example

Live Demo

```
# import the pandas library
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

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

Its **output** is as follows −

<pandas.core.groupby.DataFrameGroupBy object at 0x7fa46a977e50>

View Groups

Live Demo

```
# import the pandas library
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)
```

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

Its **output** is as follows −

```
{'Kings': Int64Index([4, 6, 7],      dtype='int64'),
'Devils': Int64Index([2, 3],         dtype='int64'),
'Riders': Int64Index([0, 1, 8, 11],  dtype='int64'),
'Royals': Int64Index([9, 10],        dtype='int64'),
'kings' : Int64Index([5],            dtype='int64')}
```

Example

Group by with multiple columns −

Live Demo

```
# import the pandas library
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

print df.groupby(['Team','Year']).groups
```

Its **output** is as follows −

```
{('Kings', 2014): Int64Index([4], dtype='int64'),
 ('Royals', 2014): Int64Index([9], dtype='int64'),
 ('Riders', 2014): Int64Index([0], dtype='int64'),
 ('Riders', 2015): Int64Index([1], dtype='int64'),
 ('Kings', 2016): Int64Index([6], dtype='int64'),
 ('Riders', 2016): Int64Index([8], dtype='int64'),
 ('Riders', 2017): Int64Index([11], dtype='int64'),
 ('Devils', 2014): Int64Index([2], dtype='int64'),
 ('Devils', 2015): Int64Index([3], dtype='int64'),
```

```
('kings', 2015): Int64Index([5], dtype='int64'),
('Royals', 2015): Int64Index([10], dtype='int64'),
('Kings', 2017): Int64Index([7], dtype='int64')}
```

Iterating through Groups

With the **groupby** object in hand, we can iterate through the object similar to itertools.obj.

Live Demo

```
# import the pandas library
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

grouped = df.groupby('Year')

for name,group in grouped:
   print name
   print group
```

Its **output** is as follows −

```
2014
   Points  Rank     Team   Year
0     876     1   Riders   2014
2     863     2   Devils   2014
4     741     3   Kings    2014
9     701     4   Royals   2014

2015
   Points  Rank     Team   Year
1     789     2   Riders   2015
```

```
3     673     3   Devils   2015
5     812     4    kings   2015
10     804     1   Royals   2015

2016
    Points  Rank     Team    Year
6     756     1    Kings   2016
8     694     2   Riders   2016

2017
    Points  Rank    Team    Year
7     788     1   Kings   2017
11     690     2  Riders   2017
```

By default, the **groupby** object has the same label name as the group name.

Select a Group

Using the **get_group()** method, we can select a single group.

Live Demo

```
# import the pandas library
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

grouped = df.groupby('Year')
print grouped.get_group(2014)
```

Its **output** is as follows −

```
  Points  Rank     Team     Year
0     876     1   Riders    2014
```

```
2     863     2   Devils    2014
4     741     3   Kings     2014
9     701     4   Royals    2014
```

Aggregations

An aggregated function returns a single aggregated value for each group. Once the **group by** object is created, several aggregation operations can be performed on the grouped data.

An obvious one is aggregation via the aggregate or equivalent **agg** method −

Live Demo

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

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

grouped = df.groupby('Year')
print grouped['Points'].agg(np.mean)
```

Its **output** is as follows −

```
Year
2014   795.25
2015   769.50
2016   725.00
2017   739.00
Name: Points, dtype: float64
```

Another way to see the size of each group is by applying the size() function −

Live Demo

```
import pandas as pd
import numpy as np

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

Attribute Access in Python Pandas
grouped = df.groupby('Team')
print grouped.agg(np.size)
```

Its **output** is as follows −

```
         Points   Rank   Year
Team
Devils        2      2      2
Kings         3      3      3
Riders        4      4      4
Royals        2      2      2
kings         1      1      1
```

Applying Multiple Aggregation Functions at Once

With grouped Series, you can also pass a **list** or **dict of functions** to do aggregation with, and generate DataFrame as output −

Live Demo

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

```
ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

grouped = df.groupby('Team')
print grouped['Points'].agg([np.sum, np.mean, np.std])
```

Its **output** is as follows −

```
Team      sum      mean          std
Devils   1536   768.000000   134.350288
Kings    2285   761.666667    24.006943
Riders   3049   762.250000    88.567771
Royals   1505   752.500000    72.831998
kings     812   812.000000          NaN
```

Transformations

Transformation on a group or a column returns an object that is indexed the same size as that is being grouped. Thus, the transform should return a result that is the same size as that of a group chunk.

Live Demo

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

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)
```

```
grouped = df.groupby('Team')
score = lambda x: (x - x.mean()) / x.std()*10
print grouped.transform(score)
```

Its **output** is as follows −

```
       Points        Rank        Year
0   12.843272  -15.000000  -11.618950
1   3.020286    5.000000   -3.872983
2   7.071068   -7.071068   -7.071068
3  -7.071068    7.071068    7.071068
4  -8.608621   11.547005  -10.910895
5        NaN         NaN        NaN
6  -2.360428   -5.773503    2.182179
7  10.969049   -5.773503    8.728716
8  -7.705963    5.000000    3.872983
9  -7.071068    7.071068   -7.071068
10  7.071068   -7.071068    7.071068
11 -8.157595    5.000000   11.618950
```

Filtration

Filtration filters the data on a defined criteria and returns the subset of data. The **filter()** function is used to filter the data.

Live Demo

```
import pandas as pd
import numpy as np

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year':
[2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017],
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

print df.groupby('Team').filter(lambda x: len(x) >= 3)
```

Its **output** is as follows −

```
   Points  Rank     Team   Year
0      876     1   Riders   2014
1      789     2   Riders   2015
4      741     3   Kings    2014
6      756     1   Kings    2016
7      788     1   Kings    2017
8      694     2   Riders   2016
11     690     2   Riders   2017
```

In the above filter condition, we are asking to return the teams which have participated three or more times in the IPL.

Chapter - 21 : Merging/Joining

Pandas has full-featured, high performance in-memory join operations idiomatically very similar to relational databases like SQL.

Pandas provides a single function, **merge**, as the entry point for all standard database join operations between DataFrame objects −

pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=True)

Here, we have used the following parameters −

1. **left** − A DataFrame object.
2. **right** − Another DataFrame object.
3. **on** − Columns (names) to join on. Must be found in both the left and right DataFrame objects.
4. **left_on** − Columns from the left DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame.

5. **right_on** − Columns from the right DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame.
6. **left_index** − If **True,** use the index (row labels) from the left DataFrame as its join key(s). In case of a DataFrame with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame.
7. **right_index** − Same usage as **left_index** for the right DataFrame.
8. **how** − One of 'left', 'right', 'outer', 'inner'. Defaults to inner. Each method has been described below.
9. **sort** − Sort the result DataFrame by the join keys in lexicographical order. Defaults to True, setting to False will improve the performance substantially in many cases.

Let us now create two different DataFrames and perform the merging operations on it.

Live Demo

```
# import the pandas library
import pandas as pd
left = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame(
   {'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print left
print right
```

Its **output** is as follows −

```
    Name  id   subject_id
0   Alex   1         sub1
1    Amy   2         sub2
2  Allen   3         sub4
```

```
3  Alice   4        sub6
4  Ayoung  5        sub5
```

```
     Name  id   subject_id
0  Billy   1        sub2
1  Brian   2        sub4
2  Brand   3        sub3
3  Bryce   4        sub6
4  Betty   5        sub5
```

Merge Two DataFrames on a Key

Live Demo

```
import pandas as pd
left = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame({
                'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print pd.merge(left,right,on='id')
```

Its **output** is as follows −

```
   Name_x   id  subject_id_x   Name_y   subject_id_y
0  Alex      1         sub1    Billy          sub2
1  Amy       2         sub2    Brian          sub4
2  Allen     3         sub4    Bran           sub3
3  Alice     4         sub6    Bryce          sub6
4  Ayoung    5         sub5    Betty          sub5
```

Merge Two DataFrames on Multiple Keys

Live Demo

```
import pandas as pd
left = pd.DataFrame({
```

```
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame({
                'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print pd.merge(left,right,on=['id','subject_id'])
```

Its **output** is as follows −

```
    Name_x   id   subject_id   Name_y
0    Alice    4         sub6    Bryce
1   Ayoung    5         sub5    Betty
```

Merge Using 'how' Argument

The **how** argument to merge specifies how to determine which keys are to be included in the resulting table. If a key combination does not appear in either the left or the right tables, the values in the joined table will be NA.

Here is a summary of the **how** options and their SQL equivalent names −

Merge Method	SQL Equivalent	Description
left	LEFT OUTER JOIN	Use keys from left object
right	RIGHT OUTER JOIN	Use keys from right object
outer	FULL OUTER JOIN	Use union of keys
inner	INNER JOIN	Use intersection of keys

Left Join

Live Demo

```
import pandas as pd
left = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print pd.merge(left, right, on='subject_id', how='left')
```

Its **output** is as follows −

```
    Name_x   id_x   subject_id   Name_y   id_y
0     Alex      1         sub1      NaN    NaN
1      Amy      2         sub2    Billy    1.0
2    Allen      3         sub4    Brian    2.0
3    Alice      4         sub6    Bryce    4.0
4   Ayoung      5         sub5    Betty    5.0
```

Right Join

Live Demo

```
import pandas as pd
left = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print pd.merge(left, right, on='subject_id', how='right')
```

Its **output** is as follows −

```
    Name_x  id_x   subject_id   Name_y   id_y
```

```
0     Amy   2.0       sub2    Billy     1
1    Allen   3.0       sub4    Brian     2
2    Alice   4.0       sub6    Bryce     4
3   Ayoung   5.0       sub5    Betty     5
4      NaN   NaN       sub3     Bran     3
```

Outer Join

[Live Demo]

```
import pandas as pd
left = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print pd.merge(left, right, how='outer', on='subject_id')
```

Its **output** is as follows −

```
  Name_x  id_x   subject_id   Name_y   id_y
0     Alex   1.0       sub1      NaN    NaN
1      Amy   2.0       sub2    Billy    1.0
2    Allen   3.0       sub4    Brian    2.0
3    Alice   4.0       sub6    Bryce    4.0
4   Ayoung   5.0       sub5    Betty    5.0
5      NaN   NaN       sub3     Bran    3.0
```

Inner Join

Joining will be performed on index. Join operation honours the object on which it is called. So, **a.join(b)** is not equal to **b.join(a)**.

[Live Demo]

```
import pandas as pd
left = pd.DataFrame({
```

```
   'id':[1,2,3,4,5],
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5']})
right = pd.DataFrame({
   'id':[1,2,3,4,5],
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5']})
print pd.merge(left, right, on='subject_id', how='inner')
```

Its **output** is as follows −

```
    Name_x   id_x   subject_id   Name_y   id_y
0     Amy      2        sub2    Billy      1
1    Allen     3        sub4    Brian      2
2    Alice     4        sub6    Bryce      4
3   Ayoung     5        sub5    Betty      5
```

Chapter - 22 : Concatenation

Pandas provides various facilities for easily combining Series**, DataFrame**, and **Panel** objects.

pd.concat(objs,axis=0,join='outer',join_axes=None,
ignore_index=False)

1. **objs** − This is a sequence or mapping of Series, DataFrame, or Panel objects.
2. **axis** − {0, 1, ...}, default 0. This is the axis to concatenate along.
3. **join** − {‘inner’, ‘outer’}, default ‘outer’. How to handle indexes on other axes(es). Outer for union and inner for intersection.
4. **ignore_index** − boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labelled 0, ..., n - 1.

5. **join_axes** − This is the list of Index objects. Specific indexes to use for the other (n-1) axes instead of performing inner/outer set logic.

Concatenating Objects

The **concat** function does all of the heavy lifting of performing concatenation operations along an axis. Let us create different objects and do concatenation.

Live Demo

```
import pandas as pd

one = pd.DataFrame({
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5'],
   'Marks_scored':[98,90,87,69,78]},
   index=[1,2,3,4,5])

two = pd.DataFrame({
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5'],
   'Marks_scored':[89,80,79,97,88]},
   index=[1,2,3,4,5])
print pd.concat([one,two])
```

Its **output** is as follows −

```
    Marks_scored     Name   subject_id
1           98     Alex        sub1
2           90      Amy        sub2
3           87    Allen        sub4
4           69    Alice        sub6
5           78   Ayoung        sub5
1           89    Billy       sub2
2           80    Brian        sub4
3           79     Bran        sub3
4           97    Bryce        sub6
```

```
5           88    Betty        sub5
```

Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this by using the **keys** argument −

Live Demo

```
import pandas as pd

one = pd.DataFrame({
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5'],
   'Marks_scored':[98,90,87,69,78]},
   index=[1,2,3,4,5])

two = pd.DataFrame({
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5'],
   'Marks_scored':[89,80,79,97,88]},
   index=[1,2,3,4,5])
print pd.concat([one,two],keys=['x','y'])
```

Its **output** is as follows −

```
x  1  98    Alex    sub1
   2  90    Amy     sub2
   3  87    Allen   sub4
   4  69    Alice   sub6
   5  78    Ayoung  sub5
y  1  89    Billy   sub2
   2  80    Brian   sub4
   3  79    Bran    sub3
   4  97    Bryce   sub6
   5  88    Betty   sub5
```

The index of the resultant is duplicated; each index is repeated.

If the resultant object has to follow its own indexing, set **ignore_index** to **True**.

Live Demo

```
import pandas as pd

one = pd.DataFrame({
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5'],
   'Marks_scored':[98,90,87,69,78]},
   index=[1,2,3,4,5])

two = pd.DataFrame({
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5'],
   'Marks_scored':[89,80,79,97,88]},
   index=[1,2,3,4,5])
print pd.concat([one,two],keys=['x','y'],ignore_index=True)
```

Its **output** is as follows −

```
    Marks_scored     Name    subject_id
0            98     Alex          sub1
1            90      Amy          sub2
2            87    Allen          sub4
3            69    Alice          sub6
4            78   Ayoung          sub5
5            89    Billy          sub2
6            80    Brian          sub4
7            79     Bran          sub3
8            97    Bryce          sub6
9            88    Betty          sub5
```

Observe, the index changes completely and the Keys are also overridden.

If two objects need to be added along **axis=1**, then the new columns will be appended.

Live Demo

```
import pandas as pd

one = pd.DataFrame({
```

```
  'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
  'subject_id':['sub1','sub2','sub4','sub6','sub5'],
  'Marks_scored':[98,90,87,69,78]},
  index=[1,2,3,4,5])

two = pd.DataFrame({
  'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
  'subject_id':['sub2','sub4','sub3','sub6','sub5'],
  'Marks_scored':[89,80,79,97,88]},
  index=[1,2,3,4,5])
print pd.concat([one,two],axis=1)
```

Its **output** is as follows −

```
   Marks_scored    Name  subject_id   Marks_scored    Name   subject_id
1           98      Alex      sub1         89         Billy         sub2
2           90       Amy      sub2         80         Brian         sub4
3           87     Allen      sub4         79          Bran         sub3
4           69     Alice      sub6         97         Bryce         sub6
5           78    Ayoung      sub5         88         Betty         sub5
```

Concatenating Using append

A useful shortcut to concat are the append instance methods on Series and DataFrame. These methods actually predated concat. They concatenate along **axis=0**, namely the index −

Live Demo

```
import pandas as pd

one = pd.DataFrame({
  'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
  'subject_id':['sub1','sub2','sub4','sub6','sub5'],
  'Marks_scored':[98,90,87,69,78]},
  index=[1,2,3,4,5])

two = pd.DataFrame({
  'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
```

```
   'subject_id':['sub2','sub4','sub3','sub6','sub5'],
   'Marks_scored':[89,80,79,97,88]},
   index=[1,2,3,4,5])
print one.append(two)
```

Its **output** is as follows −

```
    Marks_scored    Name  subject_id
1           98      Alex      sub1
2           90       Amy      sub2
3           87     Allen      sub4
4           69     Alice      sub6
5           78    Ayoung      sub5
1           89     Billy      sub2
2           80     Brian      sub4
3           79      Bran      sub3
4           97     Bryce      sub6
5           88     Betty      sub5
```

The **append** function can take multiple objects as well −

Live Demo

```
import pandas as pd

one = pd.DataFrame({
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5'],
   'Marks_scored':[98,90,87,69,78]},
   index=[1,2,3,4,5])

two = pd.DataFrame({
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5'],
   'Marks_scored':[89,80,79,97,88]},
   index=[1,2,3,4,5])
print one.append([two,one,two])
```

Its **output** is as follows −

	Marks_scored	Name	subject_id
1	98	Alex	sub1
2	90	Amy	sub2
3	87	Allen	sub4
4	69	Alice	sub6
5	78	Ayoung	sub5
1	89	Billy	sub2
2	80	Brian	sub4
3	79	Bran	sub3
4	97	Bryce	sub6
5	88	Betty	sub5
1	98	Alex	sub1
2	90	Amy	sub2
3	87	Allen	sub4
4	69	Alice	sub6
5	78	Ayoung	sub5
1	89	Billy	sub2
2	80	Brian	sub4
3	79	Bran	sub3
4	97	Bryce	sub6
5	88	Betty	sub5

Time Series

Pandas provide a robust tool for working time with Time series data, especially in the financial sector. While working with time series data, we frequently come across the following −

1. Generating sequence of time
2. Convert the time series to different frequencies

Pandas provides a relatively compact and self-contained set of tools for performing the above tasks.

Get Current Time

datetime.now() gives you the current date and time.

Live Demo

```
import pandas as pd

print pd.datetime.now()
```

Its **output** is as follows −

2017-05-11 06:10:13.393147

Create a TimeStamp

Time-stamped data is the most basic type of time series data that associates values with points in time. For pandas objects, it means using the points in time. Let's take an example −

Live Demo

```
import pandas as pd

print pd.Timestamp('2017-03-01')
```

Its **output** is as follows −

2017-03-01 00:00:00

It is also possible to convert integer or float epoch times. The default unit for these is nanoseconds (since these are how Timestamps are stored). However, often epochs are stored in another unit which can be specified. Let's take another example

Live Demo

```
import pandas as pd

print pd.Timestamp(1587687255,unit='s')
```

Its **output** is as follows −

2020-04-24 00:14:15

Create a Range of Time

Live Demo

```
import pandas as pd

print pd.date_range("11:00", "13:30", freq="30min").time
```

Its **output** is as follows −

```
[datetime.time(11, 0) datetime.time(11, 30) datetime.time(12, 0)
datetime.time(12, 30) datetime.time(13, 0) datetime.time(13, 30)]
```

Change the Frequency of Time

Live Demo

```
import pandas as pd

print pd.date_range("11:00", "13:30", freq="H").time
```

Its **output** is as follows −

```
[datetime.time(11, 0) datetime.time(12, 0) datetime.time(13, 0)]
```

Converting to Timestamps

To convert a Series or list-like object of date-like objects, for example strings, epochs, or a mixture, you can use the **to_datetime** function. When passed, this returns a Series (with the same index), while a **list-like** is converted to a **DatetimeIndex**. Take a look at the following example −

Live Demo

```
import pandas as pd

print pd.to_datetime(pd.Series(['Jul 31, 2009','2010-01-10', None]))
```

Its **output** is as follows −

```
0  2009-07-31
1  2010-01-10
2         NaT
dtype: datetime64[ns]
```

NaT means **Not a Time** (equivalent to NaN)

Let's take another example.

Live Demo

```
import pandas as pd

print pd.to_datetime(['2005/11/23', '2010.12.31', None])
```

Its **output** is as follows −

```
DatetimeIndex(['2005-11-23', '2010-12-31', 'NaT'], dtype='datetime64[ns]',
freq
```

Chapter - 23 : Date Functionality

Extending the Time series, Date functionalities play a major role in financial data analysis. While working with Date data, we will frequently come across the following −

1. Generating sequence of dates
2. Convert the date series to different frequencies

Create a Range of Dates

Using the **date.range()** function by specifying the periods and the frequency, we can create the date series. By default, the frequency of range is Days.

Live Demo

```
import pandas as pd

print pd.date_range('1/1/2011', periods=5)
```

Its **output** is as follows −

```
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
'2011-01-05'],
   dtype='datetime64[ns]', freq='D')
```

Change the Date Frequency

Live Demo

```
import pandas as pd

print pd.date_range('1/1/2011', periods=5,freq='M')
```

Its **output** is as follows −

```
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-30',
'2011-05-31'],
   dtype='datetime64[ns]', freq='M')
```

bdate_range

bdate_range() stands for business date ranges. Unlike date_range(), it excludes Saturday and Sunday.

Live Demo

```
import pandas as pd

print pd.date_range('1/1/2011', periods=5)
```

Its **output** is as follows −

```
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
'2011-01-05'],
   dtype='datetime64[ns]', freq='D')
```

Observe, after 3rd March, the date jumps to 6th march excluding 4th and 5th. Just check your calendar for the days.

Convenience functions like **date_range** and **bdate_range** utilise a variety of frequency aliases. The default frequency for date_range is a calendar day while the default for bdate_range is a business day.

Live Demo

```
import pandas as pd
start = pd.datetime(2011, 1, 1)
end = pd.datetime(2011, 1, 5)
```

```
print pd.date_range(start, end)
```

Its **output** is as follows −

```
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
'2011-01-05'],
   dtype='datetime64[ns]', freq='D')
```

Offset Aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as offset aliases.

Alias	Description	Alias	Description
B	business day frequency	BQS	business quarter start frequency
D	calendar day frequency	A	annual(Year) end frequency
W	weekly frequency	BA	business year end frequency
M	month end frequency	BAS	business year start frequency
SM	semi-month end frequency	BH	business hour frequency
BM	business month end frequency	H	hourly frequency
MS	month start frequency	T, min	minutely frequency
SMS	SMS semi month start frequency	S	secondly frequency

BMS	business month start frequency	L, ms	milliseconds
Q	quarter end frequency	U, us	microseconds
BQ	business quarter end frequency	N	nanoseconds
QS	quarter start frequency		

Chapter - 24 : Timedelta

Timedeltas are differences in times, expressed in different units, for example, days, hours, minutes, seconds. They can be both positive and negative.

We can create Timedelta objects using various arguments as shown below −

String

By passing a string literal, we can create a timedelta object.

Live Demo

```
import pandas as pd

print pd.Timedelta('2 days 2 hours 15 minutes 30 seconds')
```

Its **output** is as follows −

```
2 days 02:15:30
```

Integer

By passing an integer value with the unit, an argument creates a Timedelta object.

Live Demo

```
import pandas as pd

print pd.Timedelta(6,unit='h')
```

Its **output** is as follows −

0 days 06:00:00

Data Offsets

Data offsets such as - weeks, days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds can also be used in construction.

Live Demo

```
import pandas as pd

print pd.Timedelta(days=2)
```

Its **output** is as follows −

2 days 00:00:00

to_timedelta()

Using the top-level **pd.to_timedelta**, you can convert a scalar, array, list, or series from a recognized timedelta format/ value into a Timedelta type. It will construct a Series if the input is a Series, a scalar if the input is scalar-like, otherwise will output a **TimedeltaIndex**.

Live Demo

```
import pandas as pd

print pd.Timedelta(days=2)
```

Its **output** is as follows −

2 days 00:00:00

Operations

You can operate on Series/ DataFrames and construct **timedelta64[ns]** Series through subtraction operations on **datetime64[ns]** Series, or Timestamps.

Let us now create a DataFrame with Timedelta and datetime objects and perform some arithmetic operations on it −

Live Demo

```
import pandas as pd

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))

print df
```

Its **output** is as follows −

```
            A      B
0  2012-01-01 0 days
1  2012-01-02 1 days
2  2012-01-03 2 days
```

Addition Operations

Live Demo

```
import pandas as pd

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']

print df
```

Its **output** is as follows −

```
            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

Live Demo

```
import pandas as pd

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']

print df
```

Its **output** is as follows −

```
            A      B          C          D
0 2012-01-01 0 days 2012-01-01 2012-01-01
1 2012-01-02 1 days 2012-01-03 2012-01-04
2 2012-01-03 2 days 2012-01-05 2012-01-07
```

Chapter - 25 : Categorical Data

Often in real-time, 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 is a Pandas data type.

The categorical data type is useful in the following cases −

1. A string variable consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory.
2. 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.
3. 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).

Object Creation

Categorical objects can be created in multiple ways. The different ways have been described below −

category

By specifying the dtype as "category" in pandas object creation.

Live Demo

```
import pandas as pd

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

Its **output** is as follows −

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

The number of elements passed to the series object is four, but the categories are only three. Observe the same in the output Categories.

pd.Categorical

Using the standard pandas Categorical constructor, we can create a category object.

pandas.Categorical(values, categories, ordered)

Let’s take an example −

Live Demo

```
import pandas as pd

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

Its **output** is as follows −

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

Let’s have another example −

Live Demo

```
import pandas as pd

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

Its **output** is as follows −

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

Here, the second argument signifies the categories. Thus, any value which is not present in the categories will be treated as **NaN**.

Now, take a look at the following example −

Live Demo

```
import pandas as pd
```

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

Its **output** is as follows −

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

Logically, the order means that, **a** is greater than **b** and **b** is greater than **c**.

Description

Using the **.describe()** command on the categorical data, we get similar output to a **Series** or **DataFrame** of the **type** string.

Live Demo

```
import pandas as pd
import numpy as np

cat = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c"])
df = pd.DataFrame({"cat":cat, "s":["a", "c", "c", np.nan]})

print df.describe()
print df["cat"].describe()
```

Its **output** is as follows −

```
       cat s
count    3 3
unique   2 2
top      c c
freq     2 2
count     3
unique    2
top       c
freq      2
Name: cat, dtype: object
```

Get the Properties of the Category

obj.cat.categories command is used to get the **categories of the object**.

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c"])
print s.categories
```

Its **output** is as follows −

```
Index([u'b', u'a', u'c'], dtype='object')
```

obj.ordered command is used to get the order of the object.

Live Demo

```
import pandas as pd
import numpy as np

cat = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c"])
print cat.ordered
```

Its **output** is as follows −

```
False
```

The function returned **false** because we haven't specified any order.

Renaming Categories

Renaming categories is done by assigning new values to the **series.cat.categories series.cat.categories** property.

Live Demo

```
import pandas as pd

s = pd.Series(["a","b","c","a"], dtype="category")
s.cat.categories = ["Group %s" % g for g in s.cat.categories]
print s.cat.categories
```

Its **output** is as follows −

Index([Group a', Group b', Group c'], dtype='object')

Initial categories **[a,b,c]** are updated by the **s.cat.categories** property of the object.

Appending New Categories

Using the Categorical.add.categories() method, new categories can be appended.

Live Demo

```
import pandas as pd

s = pd.Series(["a","b","c","a"], dtype="category")
s = s.cat.add_categories([4])
print s.cat.categories
```

Its **output** is as follows −

```
Index([u'a', u'b', u'c', 4], dtype='object')
```

Removing Categories

Using the **Categorical.remove_categories()** method, unwanted categories can be removed.

Live Demo

```
import pandas as pd

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

print ("After removal:")
print s.cat.remove_categories("a")
```

Its **output** is as follows −

```
Original object:
0  a
1  b
```

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

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

Comparison of Categorical Data

Comparing categorical data with other objects is possible in three cases −

1. comparing equality (== and !=) to a list-like object (list, Series, array, ...) of the same length as the categorical data.
2. all comparisons (==, !=, >, >=, <, and <=) of categorical data to another categorical Series, when ordered==True and the categories are the same.
3. all comparisons of a categorical data to a scalar.

Take a look at the following example −

Live Demo

```
import pandas as pd

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
```

Its **output** is as follows −

```
0  False
```

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

Chapter - 26 : Visualisation

Basic Plotting: plot

This functionality on Series and DataFrame is just a simple wrapper around the **matplotlib library's plot()** method.

```
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()
```

Its **output** is as follows −

If the index consists of dates, it calls **gct().autofmt_xdate()** to format the x-axis as shown in the above illustration.

We can plot one column versus another using the **x** and **y** keywords.

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 −

1. bar or bath for bar plots
2. hist for histogram
3. box for boxplot
4. 'area' for area plots
5. 'scatter' for scatter plots

Bar Plot

Let us now see what a Bar Plot is by creating one. A bar plot can be created in the following way −

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

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

Its **output** is as follows −

To produce a stacked bar plot, **pass stacked=True** −

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

Its **output** is as follows −

To get horizontal bar plots, use the **barh** method −

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

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

```
df.plot.barh(stacked=True)
```

Its **output** is as follows −

Histograms

Histograms can be plotted using the **plot.hist()** method. We can specify the number of bins.

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

```
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)
```

Its **output** is as follows −

To plot different histograms for each column, use the following code −

```
import pandas as pd
import numpy as np

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.diff.hist(bins=20)
```

Its **output** is as follows −

Box Plots

Boxplot can be drawn by calling **Series.box.plot()** and **DataFrame.box.plot()**, or **DataFrame.boxplot()** to visualise the distribution of values within each column.

For instance, here is a box plot representing five trials of 10 observations of a uniform random variable on [0,1).

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

Its **output** is as follows −

Area Plot

Area plots can be created using the **Series.plot.area()** or the **DataFrame.plot.area()** methods.

```
import pandas as pd
import numpy as np

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

Its **output** is as follows −

Scatter Plot

Scatter plot can be created using the **DataFrame.plot.scatter()** methods.

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

Its **output** is as follows −

Pie Chart

Pie charts can be created using the **DataFrame.plot.pie()** method.

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

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

Its **output** is as follows −

Chapter - 27 : IO Tools

The **Pandas I/O API** is a set of top level reader functions accessed like **pd.read_csv()** that generally return a Pandas object.

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 −

```
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

Here is how the **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
```

Save this data as **temp.csv** and conduct operations on it.


```
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
```

Save this data as **temp.csv** and conduct operations on it.

read.csv

read.csv reads data from the csv files and creates a DataFrame object.

```
import pandas as pd
```

```
df=pd.read_csv("temp.csv")
print df
```

Its **output** is as follows −

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

custom index

This specifies a column in the csv file to customise the index using **index_col.**

```
import pandas as pd

df=pd.read_csv("temp.csv",index_col=['S.No'])
print df
```

Its **output** is as follows −

```
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
```

Converters

dtype of the columns can be passed as a dict.

```
import pandas as pd

df = pd.read_csv("temp.csv", dtype={'Salary': np.float64})
print df.dtypes
```

Its **output** is as follows −

```
S.No       int64
Name      object
Age        int64
City      object
Salary   float64
dtype: object
```

By default, the **dtype** of the Salary column is **int**, but the result shows it as **float** because we have explicitly casted the type.

Thus, the data looks like float −

```
  S.No   Name   Age     City    Salary
0   1     Tom   28    Toronto   20000.0
1   2     Lee   32   HongKong    3000.0
2   3  Steven   43   Bay Area    8300.0
3   4     Ram   38  Hyderabad    3900.0
```

header_names

Specify the names of the header using the names argument.

```
import pandas as pd

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

Its **output** is as follows −

```
       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
```

Observe, the header names are appended with the custom names, but the header in the file has not been eliminated. Now, we use the header argument to remove that.

If the header is in a row other than the first, pass the row number to the header. This will skip the preceding rows.

```
import pandas as pd

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

Its **output** is as follows −

```
      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
```

skiprows

skiprows skips the number of rows specified.

```
import pandas as pd

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

Its **output** is as follows −

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

Chapter - 28 : 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”. This will make much more sense in an example. All of the standard Pandas data structures apply the **to_sparse** method −

Live Demo

```
import pandas as pd
import numpy as np

ts = pd.Series(np.random.randn(10))
ts[2:-2] = np.nan
sts = ts.to_sparse()
```

```
print sts
```

Its **output** is as follows −

```
0   -0.810497
1   -1.419954
2         NaN
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8    0.439240
9   -1.095910
dtype: float64
BlockIndex
Block locations: array([0, 8], dtype=int32)
Block lengths: array([2, 2], dtype=int32)
```

The sparse objects exist for memory efficiency reasons.

Let us now assume you had a large NA DataFrame and execute the following code −

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(10000, 4))
df.ix[:9998] = np.nan
sdf = df.to_sparse()

print sdf.density
```

Its **output** is as follows −

```
0.0001
```

Any sparse object can be converted back to the standard dense form by calling **to_dense** −

Live Demo

```
import pandas as pd
import numpy as np
ts = pd.Series(np.random.randn(10))
ts[2:-2] = np.nan
sts = ts.to_sparse()
print sts.to_dense()
```

Its **output** is as follows −

```
0   -0.810497
1   -1.419954
2         NaN
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8    0.439240
9   -1.095910
dtype: float64
```

Sparse Dtypes

Sparse data should have the same dtype as its dense representation. Currently, **float64, int64** and **blood types** are supported. Depending on the original **dtype, fill_value default** changes −

- **float64** − np.nan
- **int64** − 0
- **bool** − False

Let us execute the following code to understand the same −

Live Demo

```
import pandas as pd
import numpy as np

s = pd.Series([1, np.nan, np.nan])
print s

s.to_sparse()
print s
```

Its **output** is as follows −

```
0   1.0
1   NaN
2   NaN
dtype: float64

0   1.0
1   NaN
2   NaN
dtype: float64
```

Chapter - 29 : Caveats & Gotchas

Caveats means warning and gotcha means an unseen problem.

Using If/Truth Statement with Pandas

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 zero length? False because there are False values? It is unclear, so instead, Pandas raises a **ValueError** −

Live Demo

```
import pandas as pd
```

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

Its **output** is as follows −

```
ValueError: The truth value of a Series is ambiguous.
Use a.empty, a.bool() a.item(),a.any() or a.all().
```

In **if** condition, it is unclear what to do with it. The error is suggestive of whether to use a **None** or **any of those**.

Live Demo

```
import pandas as pd

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

Its **output** is as follows −

```
I am any
```

To evaluate single-element pandas objects in a Boolean context, use the method **.bool()** −

Live Demo

```
import pandas as pd

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

Its **output** is as follows −

```
True
```

Bitwise Boolean

Bitwise Boolean operators like == and **!**= will return a Boolean series, which is almost always what is required anyways.

Live Demo

```
import pandas as pd
```

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

Its **output** is as follows −

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

isin Operation

This returns a Boolean series showing whether each element in the Series is exactly contained in the passed sequence of values.

Live Demo

```
import pandas as pd

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

Its **output** is as follows −

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

Reindexing vs ix Gotcha

Many users will find themselves using the **ix indexing capabilities** as a concise means of selecting data from a Pandas object −

Live Demo

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

```
df = pd.DataFrame(np.random.randn(6, 4), columns=['one', 'two', 'three',
'four'],index=list('abcdef'))

print df
print df.ix[['b', 'c', 'e']]
```

Its **output** is as follows −

```
        one        two      three       four
a  -1.582025   1.335773   0.961417  -1.272084
b   1.461512   0.111372  -0.072225   0.553058
c  -1.240671   0.762185   1.511936  -0.630920
d  -2.380648  -0.029981   0.196489   0.531714
e   1.846746   0.148149   0.275398  -0.244559
f  -1.842662  -0.933195   2.303949   0.677641

        one        two      three       four
b   1.461512   0.111372  -0.072225   0.553058
c  -1.240671   0.762185   1.511936  -0.630920
e   1.846746   0.148149   0.275398  -0.244559
```

This is, of course, completely equivalent in this case to using the **reindex** method −

Live Demo

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(6, 4), columns=['one', 'two', 'three',
'four'],index=list('abcdef'))

print df
print df.reindex(['b', 'c', 'e'])
```

Its **output** is as follows −

```
        one        two      three       four
a   1.639081   1.369838   0.261287  -1.662003
b  -0.173359   0.242447  -0.494384   0.346882
c  -0.106411   0.623568   0.282401  -0.916361
```

```
d   -1.078791  -0.612607  -0.897289  -1.146893
e    0.465215   1.552873  -1.841959   0.329404
f    0.966022  -0.190077   1.324247   0.678064

          one        two      three       four
b   -0.173359   0.242447  -0.494384   0.346882
c   -0.106411   0.623568   0.282401  -0.916361
e    0.465215   1.552873  -1.841959   0.329404
```

Some might conclude that **ix** and **reindex** are 100% equivalent based on this. This is true except in the case of integer indexing. For example, the above operation can alternatively be expressed as −

Live Demo

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

df = pd.DataFrame(np.random.randn(6, 4), columns=['one', 'two', 'three',
'four'],index=list('abcdef'))

print df
print df.ix[[1, 2, 4]]
print df.reindex([1, 2, 4])
```

Its **output** is as follows −

```
          one        two      three       four
a   -1.015695  -0.553847   1.106235  -0.784460
b   -0.527398  -0.518198  -0.710546  -0.512036
c   -0.842803  -1.050374   0.787146   0.205147
d   -1.238016  -0.749554  -0.547470  -0.029045
e   -0.056788   1.063999  -0.767220   0.212476
f    1.139714   0.036159   0.201912   0.710119

          one        two      three       four
b   -0.527398  -0.518198  -0.710546  -0.512036
c   -0.842803  -1.050374   0.787146   0.205147
e   -0.056788   1.063999  -0.767220   0.212476
```

```
    one  two  three  four
1   NaN  NaN    NaN   NaN
2   NaN  NaN    NaN   NaN
4   NaN  NaN    NaN   NaN
```

It is important to remember that **reindex is strict label indexing only**. This can lead to some potentially surprising results in pathological cases where an index contains, say, both integers and strings.

Chapter - 30 : Comparison with SQL

Since many potential Pandas users have some familiarity with SQL, this page is meant to provide some examples of how various SQL operations can be performed using pandas.

```
import pandas as pd

url = 'https://raw.github.com/pandasdev/
pandas/master/pandas/tests/data/tips.csv'

tips=pd.read_csv(url)
print tips.head()
```

Its **output** is as follows −

```
   total_bill   tip     sex  smoker  daytime  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
```

SELECT

In SQL, selection is done using a comma-separated list of columns that you select (or a * to select all columns) −

```
SELECT total_bill, tip, smoker, time
FROM tips
LIMIT 5;
```

With Pandas, column selection is done by passing a list of column names to your DataFrame −

```
tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
```

Let's check the full program −

```
import pandas as pd

url = 'https://raw.github.com/pandasdev/
pandas/master/pandas/tests/data/tips.csv'

tips=pd.read_csv(url)
print tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
```

Its **output** is as follows −

```
  total_bill  tip  smoker   time
0      16.99  1.01     No   Dinner
1      10.34  1.66     No   Dinner
2      21.01  3.50     No   Dinner
3      23.68  3.31     No   Dinner
4      24.59  3.61     No   Dinner
```

Calling the DataFrame without the list of column names will display all columns (akin to SQL's *).

WHERE

Filtering in SQL is done via a WHERE clause.

```
SELECT * FROM tips WHERE time = 'Dinner' LIMIT 5;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using Boolean indexing.

```
tips[tips['time'] == 'Dinner'].head(5)
```

Let’s check the full program −

```
import pandas as pd

url = 'https://raw.github.com/pandasdev/
pandas/master/pandas/tests/data/tips.csv'

tips=pd.read_csv(url)
print tips[tips['time'] == 'Dinner'].head(5)
```

Its **output** is as follows −

```
   total_bill   tip      sex  smoker  daytime  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
```

The above statement passes a Series of True/False objects to the DataFrame, returning all rows with True.

GroupBy

This operation fetches the count of records in each group throughout a dataset. For instance, a query fetching us the number of tips left by sex −

```
SELECT sex, count(*)
FROM tips
GROUP BY sex;
```

The Pandas equivalent would be −

```
tips.groupby('sex').size()
```

Let’s check the full program −

```
import pandas as pd
```

```
url = 'https://raw.github.com/pandasdev/
pandas/master/pandas/tests/data/tips.csv'
```

```
tips=pd.read_csv(url)
print tips.groupby('sex').size()
```

Its **output** is as follows −

```
sex
Female   87
Male    157
dtype: int64
```

Top N rows

SQL returns the **top n rows** using **LIMIT** −

```
SELECT * FROM tips
LIMIT 5 ;
```

The Pandas equivalent would be −

```
tips.head(5)
```

Let’s check the full example −

```
import pandas as pd
```

```
url = 'https://raw.github.com/pandas-
dev/pandas/master/pandas/tests/data/tips.csv'
```

```
tips=pd.read_csv(url)
tips = tips[['smoker', 'day', 'time']].head(5)
print tips
```

Its **output** is as follows −

```
  smoker   day     time
0      No   Sun   Dinner
1      No   Sun   Dinner
```

2	No	Sun	Dinner
3	No	Sun	Dinner
4	No	Sun	Dinner

These are the few basic operations we compared are, which we learnt, in the previous chapters of the Pandas Library.

Thank You