1 with Python Libraries

As you already know, Python has become one of the most popular, standard languages and is a complete package for data science-based operations. Python offers numerous libraries, such as NumPy, Pandas, SciPy, Scikit-Learn, Matplotlib, Seaborn, and Plotly. These libraries provide a complete ecosystem for data analysis that is used by data analysts, data scientists, and business analysts. Python also offers other features, such as flexibility, being easy to learn, faster development, a large active community, and the ability to work on complex numeric, scientific, and research applications. All these features make it the first choice for data analysis.

In this chapter, we will focus on various data analysis processes, such as KDD, SEMMA, and CRISP-DM. After this, we will provide a comparison between data analysis and data science, as well as the roles and different skillsets for data analysts and data scientists. Finally, we will shift our focus and start installing various Python libraries, IPython, Jupyter Lab, and Jupyter Notebook. We will also look at various advanced features of Jupyter Notebooks.

In this introductory chapter, we will cover the following topics:

- Understanding data analysis
- The standard process of data analysis
- The KDD process
- SEMMA
- CRISP-DM
- Comparing data analysis and data science
- The skillsets of data analysts and data scientists
- Installing Python 3
- Software used in this book
-

Using IPython as a shell
- Using Jupyter Lab
- Using Jupyter Notebooks
- Advanced features of Jupyter Notebooks

Let's get started!

Understanding data analysis

The 21st century is the century of information. We are living in the age of information, which means that almost every aspect of our daily life is generating data. Not only this, but business operations, government operations, and social posts are also generating huge data. This data is accumulating day by day due to data being continually generated from business, government, scientific, engineering, health, social, climate, and environmental activities. In all these domains of decision-making, we need a systematic, generalized, effective, and flexible system for the analytical and scientific process so that we can gain insights into the data that is being generated.

In today's smart world, data analysis offers an effective decision-making process for business and government operations. Data analysis is the activity of inspecting, preprocessing, exploring, describing, and visualizing the given dataset. The main objective of the data analysis process is to discover the required information for decision-making. Data analysis offers multiple approaches, tools, and techniques, all of which can be applied to diverse domains such as business, social science, and fundamental science.

Let's look at some of the core fundamental data analysis libraries of the Python ecosystem:

- **NumPy**: This is a short form of numerical Python. It is the most powerful scientific library available in Python for handling multidimensional arrays, matrices, and methods in order to compute mathematics efficiently.
- **SciPy**: This is also a powerful scientific computing library for performing scientific, mathematical, and engineering operations.
- **Pandas**: This is a data exploration and manipulation library that offers tabular data structures such as DataFrames and various methods for data analysis and manipulation.
- **Scikit-learn**: This stands for "Scientific Toolkit for Machine learning". It is a machine learning library that offers a variety of supervised and unsupervised

algorithms, such as regression, classification, dimensionality reduction, cluster analysis, and anomaly detection.

- **Matplotlib**: This is a core data visualization library and is the base library for all other visualization libraries in Python. It offers 2D and 3D plots, graphs, charts, and figures for data exploration. It runs on top of NumPy and SciPy.
- **Seaborn**: This is based on Matplotlib and offers easy to draw, high-level, interactive, and more organized plots.
- **Plotly**: Plotly is a data visualization library. It offers high quality and interactive graphs, such as scatter charts, line charts, bar charts, histograms, boxplots, heatmaps, and subplots.

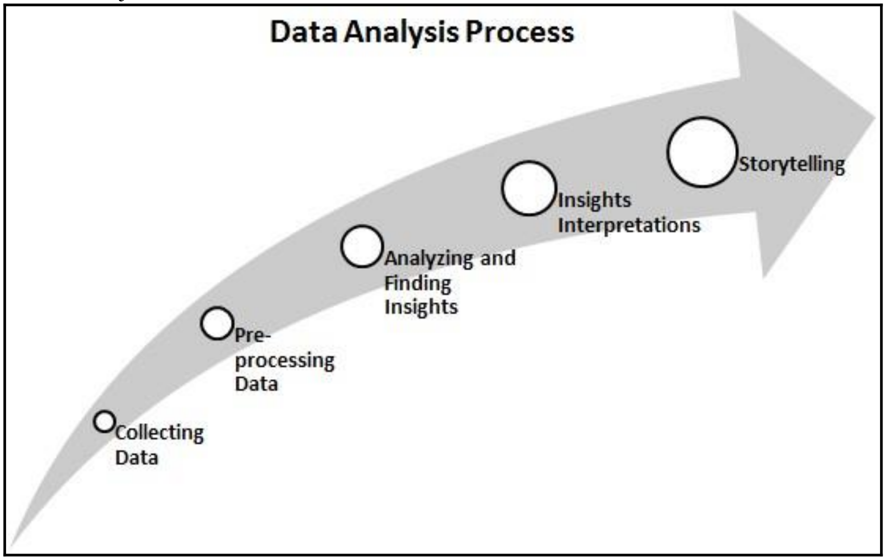
Installation instructions for the required libraries and software will be provided throughout this book when they're needed. In the meantime, let's discuss various data analysis processes, such as the standard process, KDD, SEMMA, and CRISP-DM.

The standard process of data analysis

Data analysis refers to investigating the data, finding meaningful insights from it, and drawing conclusions. The main goal of this process is to collect, filter, clean, transform, explore, describe, visualize, and communicate the insights from this data to discover decision-making information. Generally, the data analysis process is comprised of the following phases:

1. **Collecting Data**: Collect and gather data from several sources.
2. **Preprocessing Data**: Filter, clean, and transform the data into the required format.
3. **Analyzing and Finding Insights**: Explore, describe, and visualize the data and find insights and conclusions.
4. **Insights Interpretations**: Understand the insights and find the impact each variable has on the system.
5. **Storytelling**: Communicate your results in the form of a story so that a layman can understand them.

We can summarize these steps of the data analysis process via the following process diagram:



In this section, we have covered the standard data analysis process, which emphasizes finding interpretable insights and converting them into a user story. In the next section, we will discuss the KDD process.

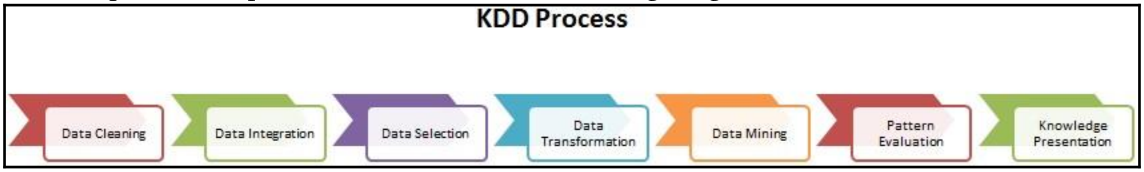
The KDD process

The **KDD** acronym stands for **knowledge discovery from data** or **Knowledge Discovery in Databases**. Many people treat KDD as one synonym for data mining. Data mining is referred to as the knowledge discovery process of interesting patterns. The main objective of KDD is to extract or discover hidden interesting patterns from large databases, data warehouses, and other web and information repositories. The KDD process has seven major phases:

1. **Data Cleaning**: In this first phase, data is preprocessed. Here, noise is removed, missing values are handled, and outliers are detected.
2. **Data Integration**: In this phase, data from different sources is combined and integrated together using data migration and ETL tools.
3. **Data Selection**: In this phase, relevant data for the analysis task is recollected.

4. **Data Transformation**: In this phase, data is engineered in the required appropriate form for analysis.
5. **Data Mining**: In this phase, data mining techniques are used to discover useful and unknown patterns.
6. **Pattern Evaluation**: In this phase, the extracted patterns are evaluated.
7. **Knowledge Presentation**: After pattern evaluation, the extracted knowledge needs to be visualized and presented to business people for decision-making purposes.

The complete KDD process is shown in the following diagram:



KDD is an iterative process for enhancing data quality, integration, and transformation to get a more improved system. Now, let's discuss the SEMMA process.

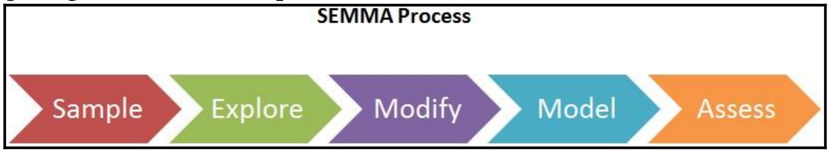
SEMMA

The **SEMMA** acronym's full form is **Sample**, **Explore**, **Modify**, **Model**, and **Assess**. This sequential data mining process is developed by SAS. The SEMMA process has five major phases:

1. **Sample**: In this phase, we identify different databases and merge them. After this, we select the data sample that's sufficient for the modeling process.
2. **Explore**: In this phase, we understand the data, discover the relationships among variables, visualize the data, and get initial interpretations.
3. **Modify**: In this phase, data is prepared for modeling. This phase involves dealing with missing values, detecting outliers, transforming features, and creating new additional features.
4. **Model**: In this phase, the main concern is selecting and applying different modeling techniques, such as linear and logistic regression, backpropagation networks, KNN, support vector machines, decision trees, and Random Forest.

5. **Assess**: In this last phase, the predictive models that have been developed are evaluated using performance evaluation measures.

The following diagram shows this process:



The preceding diagram shows the steps involved in the SEMMA process. SEMMA emphasizes model building and assessment. Now, let's discuss the CRISP-DM process.

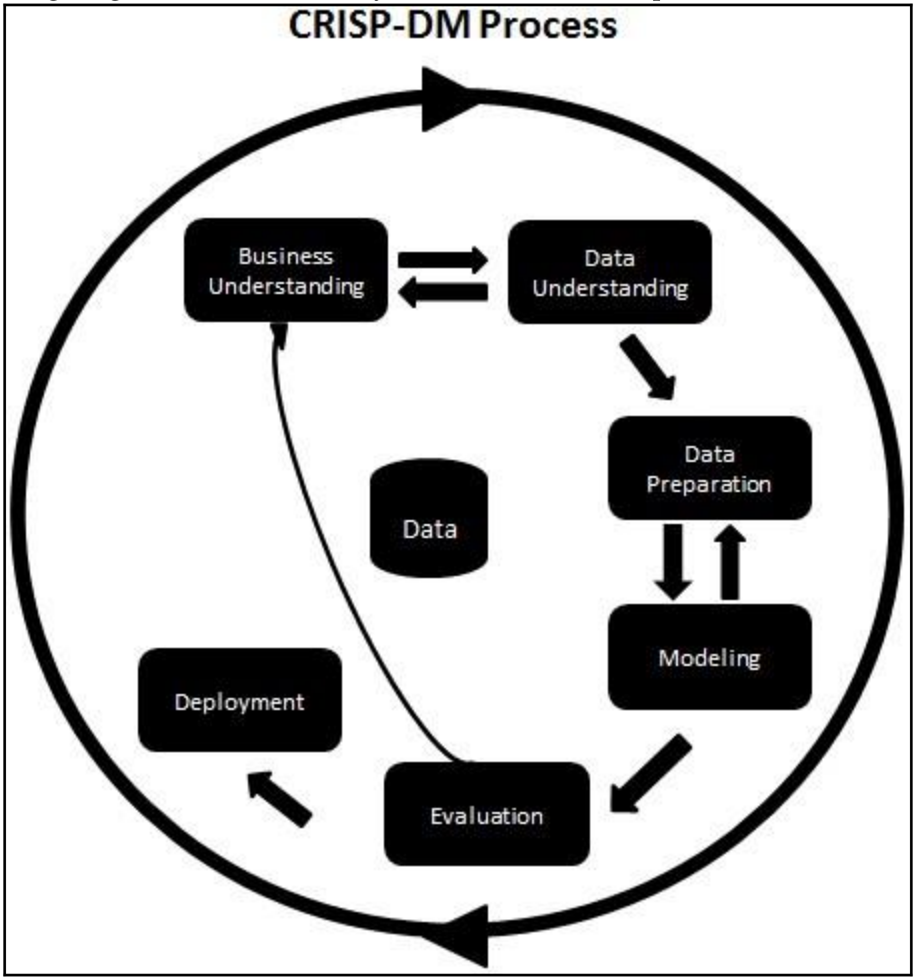
CRISP-DM

CRISP-DM's full form is **CRoss-InduStry Process for Data Mining**. CRISP-DM is a welldefined, well-structured, and well-proven process for machine learning, data mining, and business intelligence projects. It is a robust, flexible, cyclic, useful, and practical approach to solving business problems. The process discovers hidden valuable information or patterns from several databases. The CRISP-DM process has six major phases:

1. **Business Understanding**: In this first phase, the main objective is to understand the business scenario and requirements for designing an analytical goal and initial action plan.
2. **Data Understanding:** In this phase, the main objective is to understand the data and its collection process, perform data quality checks, and gain initial insights.
3. **Data Preparation**: In this phase, the main objective is to prepare analytics-ready data. This involves handling missing values, outlier detection and handling, normalizing data, and feature engineering. This phase is the most timeconsuming for data scientists/analysts.
4. **Modeling**: This is the most exciting phase of the whole process since this is where you design the model for prediction purposes. First, the analyst needs to decide on the modeling technique and develop models based on data.
5. **Evaluation:** Once the model has been developed, it's time to assess and test the model's performance on validation and test data using model evaluation measures such as MSE, RMSE, R-Square for regression and accuracy, precision, recall, and the F1-measure.

6. **Deployment**: In this final phase, the model that was chosen in the previous step will be deployed to the production environment. This requires a team effort from data scientists, software developers, DevOps experts, and business professionals.

The following diagram shows the full cycle of the CRISP-DM process:



The standard process focuses on discovering insights and making interpretations in the form of a story, while KDD focuses on data-driven pattern discovery and visualizing this. SEMMA majorly focuses on model building tasks, while CRISP-DM focuses on business understanding and deployment. Now that we know about some of the processes surrounding data analysis, let's compare data analysis and data science to find out how they are related, as well as what makes them different from one other.

Comparing data analysis and data science

Data analysis is the process in which data is explored in order to discover patterns that help us make business decisions. It is one of the subdomains of data science. Data analysis methods and tools are widely utilized in several business domains by business analysts, data scientists, and researchers. Its main objective is to improve productivity and profits. Data analysis extracts and queries data from different sources, performs exploratory data analysis, visualizes data, prepares reports, and presents it to the business decisionmaking authorities.

On the other hand, data science is an interdisciplinary area that uses a scientific approach to extract insights from structured and unstructured data. Data science is a union of all terms, including data analytics, data mining, machine learning, and other related domains. Data science is not only limited to exploratory data analysis and is used for developing models and prediction algorithms such as stock price, weather, disease, fraud forecasts, and recommendations such as movie, book, and music recommendations.

The roles of data analysts and data scientists

A data analyst collects, filters, processes, and applies the required statistical concepts to capture patterns, trends, and insights from data and prepare reports for making decisions. The main objective of the data analyst is to help companies solve business problems using discovered patterns and trends. The data analyst also assesses the quality of the data and handles the issues concerning data acquisition. A data analyst should be proficient in writing SQL queries, finding patterns, using visualization tools, and using reporting tools Microsoft Power BI, IBM Cognos, Tableau, QlikView, Oracle BI, and more.

Data scientists are more technical and mathematical than data analysts. Data scientists are research- and academic-oriented, whereas data analysts are more application-oriented. Data scientists are expected to predict a future event, whereas data analysts extract significant insights out of data. Data scientists develop their own questions, while data analysts find answers to given questions. Finally, data scientists focus on **what is going to happen**, whereas data analysts focus on **what has happened so far**. We can summarize these two roles using the following table:

Features	**Data Scientist**	**Data Analyst**

Background	Predict future events and scenarios based on data	Discover meaningful insights from the data.
Role	Formulate questions that can profit the business	Solve the business questions to make decisions.
Type of data	Work on both structured and unstructured data	Only work on structured data
Programming	Advanced programming	Basic programming
Skillset	Knowledge of statistics, machine learning algorithms, NLP, and deep learning	Knowledge of statistics, SQL, and data visualization
Tools	R, Python, SAS, Hadoop, Spark, TensorFlow, and Keras	Excel, SQL, R, Tableau, and QlikView

Now that we know what defines a data analyst and data scientist, as well as how they are different from each other, let's have a look at the various skills that you would need to become one of them.

The skillsets of data analysts and data scientists

A data analyst is someone who discovers insights from data and creates value out of it. This helps decision-makers understand how the business is performing. Data analysts must acquire the following skills:

- **Exploratory Data Analysis (EDA)**: EDA is an essential skill for data analysts. It helps with inspecting data to discover patterns, test hypotheses, and assure assumptions.
- **Relational Database**: Knowledge of at least one of the relational database tools, such as MySQL or Postgre, is mandatory. SQL is a must for working on relational databases.
- **Visualization and BI Tools**: A picture speaks more than words. Visuals have more of an impact on humans and visuals are a clear and easy option for representing the insights. Visualization and BI tools such as Tableau, QlikView,

MS Power BI, and IBM Cognos can help analysts visualize and prepare reports.
Spreadsheet: Knowledge of MS Excel, WPS, Libra, or Google Sheets is mandatory for storing and managing data in tabular form.

Storytelling and Presentation Skills: The art of storytelling is another necessary skill. A data analyst should be an expert in connecting data facts to an idea or an incident and turning it into a story.

On the other hand, the primary job of a data scientist is to solve problems using data. In order to do this, they need to understand the client's requirements, their domain, their problem space, and ensure that they get exactly what they really want. The tasks that data scientists undertake vary from company to company. Some companies use data analysts and offer the title of data scientist just to glorify the job designation. Some combine data analyst tasks with data engineers and offer data scientists designation; others assign them to machine learning-intensive tasks with data visualizations.

The task of the data scientist varies, depending on the company. Some employ data scientists as well-known data analysts and combine their responsibilities with data engineers. Others give them the task of performing intensive data visualization on machines.

A data scientist has to be a jack of all trades and wear multiple hats, including those of a data analyst, statistician, mathematician, programmer, ML, or NLP engineer. Most people are not skilled enough or experts in all these trades. Also, getting skilled enough requires lots of effort and patience. This is why data science cannot be learned in 3 or 6 months. Learning data science is a journey. A data scientist should have a wide variety of skills, such as the following:

- **Mathematics and Statistics**: Most machine learning algorithms are based on mathematics and statistics. Knowledge of mathematics helps data scientists develop custom solutions.
- **Databases**: Knowledge of SQL allows data scientists to interact with the database and collect the data for prediction and recommendation.
- **Machine Learning**: Knowledge of supervised machine learning techniques such as regression analysis, classification techniques, and unsupervised machine learning techniques such as cluster analysis, outlier detection, and dimensionality reduction.

- **Programming Skills**: Knowledge of programming helps data scientists automate their suggested solutions. Knowledge of Python and R is
- recommended. **Storytelling and Presentation skills**: Communicating the results in the form of storytelling via PowerPoint presentations.
- **Big Data Technology**: Knowledge of big data platforms such as Hadoop and Spark helps data scientists develop big data solutions for large-scale enterprises.
- **Deep Learning Tools**: Deep learning tools such as Tensorflow and Keras are utilized in NLP and image analytics.

Apart from these skillsets, knowledge of web scraping packages/tools for extracting data from diverse sources and web application frameworks such as Flask or Django for designing prototype solutions is also obtained. It is all about the skillset for data science professionals.

Now that we have covered the basics of data analysis and data science, let's dive into the basic setup needed to get started with data analysis. In the next section, we'll learn how to install Python.

2 NumPy and pandas

Now that we have understood data analysis, its process, and its installation on different platforms, it's time to learn about NumPy arrays and `pandas` DataFrames. This chapter acquaints you with the fundamentals of NumPy arrays and `pandas` DataFrames. By the end of this chapter, you will have a basic understanding of NumPy arrays, and `pandas` DataFrames and their related functions.

`pandas` is named after panel data (an econometric term) and Python data analysis and is a popular open-source Python library. We shall learn about basic `pandas` functionalities, data structures, and operations in this chapter. The official `pandas` documentation insists on naming the project `pandas` in all lowercase letters. The other convention the `pandas` project insists on is the `import pandas as pd` import statement.

In this chapter, our focus will be on the following topics:

- Understanding NumPy arrays
- NumPy array numerical data types
- Manipulating array shapes
- The stacking of NumPy arrays
- Partitioning NumPy arrays
- Changing the data type of NumPy arrays
- Creating NumPy views and copies
- Slicing NumPy arrays
- Boolean and fancy indexing
- Broadcasting arrays
- Creating `pandas` DataFrames
- Understanding `pandas` Series
- Reading and querying the Quandl data
- Describing `pandas` DataFrames

- Grouping and joining `pandas` DataFrames
- Working with missing values
- Creating pivot tables
- Dealing with dates

Understanding NumPy arrays

NumPy can be installed on a PC using `pip` or `brew` but if the user is using the Jupyter Notebook, then there is no need to install it. NumPy is already installed in the Jupyter Notebook. I will suggest to you to please use the Jupyter Notebook as your IDE because we are executing all the code in the Jupyter Notebook. We have already shown in `Chapter 1`, *Getting Started with Python Libraries*, how to install Anaconda, which is a complete suite for data analysis. NumPy arrays are a series of homogenous items. Homogenous means the array will have all the elements of the same data type. Let's create an array using NumPy. You can create an array using the `array()` function with a list of items. Users can also fix the data type of an array. Possible data types are `bool`, `int`, `float`, `long`, `double`, and `long double`.

Let's see how to create an empty array:

```
# Creating an array
import numpy as np a =
np.array([2,4,6,8,10])

print(a)

Output:
[ 2 4 6 8 10]
```

Another way to create a NumPy array is with `arange()`. It creates an evenly spaced NumPy array. Three values – start, stop, and step – can be passed to the `arange(start,[stop],step)` function. The start is the initial value of the range, the stop is the last value of the range, and the step is the increment in that range. The stop parameter is compulsory. In the following example, we have used `1` as the start and `11` as the stop parameter. The `arange(1,11)` function will return 1 to 10 values with one step because the step is, by default, 1. The `arrange()` function generates a value that is one less than the stop parameter value. Let's understand this through the following example:

```
# Creating an array using arange()
import numpy as np
a =
```

```
np.arange(1,11)
print(a)
```

Output:

```
[ 1 2 3 4 5 6 7 8 9 10]
```

Apart from the `array()` and `arange()` functions, there are other options, such as `zeros()`, `ones()`, `full()`, `eye()`, and `random()`, which can also be used to create a NumPy array, as these functions are initial placeholders. Here is a detailed description of each function:

- `zeros()`: The `zeros()` function creates an array for a given dimension with all zeroes.
- `ones()`: The `ones()` function creates an array for a given dimension with all ones. `fulls()`: The `full()` function generates an array with constant
- values. `eyes()`: The `eye()` function creates an identity matrix.
- `random()`: The `random()` function creates an array with any given dimension.
-

Let's understand these functions through the following example:

```
import numpy as np

# Create an array of all zeros
p =
np.zeros((3,3))print(p)

# Create an array of all ones
q =
np.ones((2,2))print(q)

# Create a constant array
r = np.full((2,2), 4)
print(r)

# Create a 2x2 identity matrix
s = np.eye(4)print(s)

# Create an array filled with random values
t =
np.random.random((3,3))prin
t(t)
```

This results in the following output:

```
[[0. 0. 0.]
 [0. 0. 0.]
```

```
[0. 0. 0.]]

[[1. 1.]
[1. 1.]]

[[4 4]
 [4 4]]

[[1. 0. 0. 0.]
 [0. 1. 0. 0.]
 [0. 0. 1. 0.]
[0. 0. 0. 1.]]

[[0.16681892 0.00398631 0.61954178]
 [0.52461924 0.30234715 0.58848138]
 [0.75172385 0.17752708 0.12665832]]
```

In the preceding code, we have seen some built-in functions for creating arrays with allzero values, all-one values, and all-constant values. After that, we have created the identity matrix using the `eye()` function and a random matrix using the `random.random()` function. Let's see some other array features in the next section.

Array features

In general, NumPy arrays are a homogeneous kind of data structure that has the same types of items. The main benefit of an array is its certainty of storage size because of its same type of items. A Python list uses a loop to iterate the elements and perform operations on them. Another benefit of NumPy arrays is to offer vectorized operations instead of iterating each item and performing operations on it. NumPy arrays are indexed just like a Python list and start from 0. NumPy uses an optimized C API for the fast processing of the array operations.

Let's make an array using the `arange()` function, as we did in the previous section, and let's check its data type:

```
# Creating an array using arange()
import numpy as np
a =
np.arange(1,11)

print(type(a))
print(a.dtype)

Output:
<class 'numpy.ndarray'>
int64
```

When you use `type()`, it returns `numpy.ndarray`. This means that the `type()` function returns the type of the container. When you use `dtype()`, it will return `int64`, since it is the type of the elements. You may also get the output as `int32` if you are using 32-bit Python. Both cases use integers (32- and 64-bit). One-dimensional NumPy arrays are also known as vectors.

Let's find out the shape of the vector that we produced a few minutes ago:

```
print(a.shape)
Output: (10,)
```

As you can see, the vector has 10 elements with values ranging from 1 to 10. The `shape` property of the array is a tuple; in this instance, it is a tuple of one element, which holds the length in each dimension.

Selecting array elements

In this section, we will see how to select the elements of the array. Let's see an example of a 2*2 matrix:

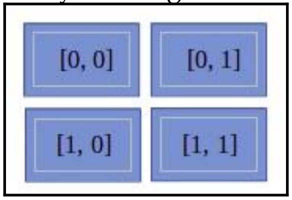
```
a = np.array([[5,6],[7,8]])
print(a)

Output:
[[5 6]
 [7 8]]
```

In the preceding example, the matrix is created using the `array()` function with the input list of lists.

Selecting array elements is pretty simple. We just need to specify the index of the matrix as `a[m,n]`. Here, `m` is the row index and `n` is the column index of the matrix. We will now select each item of the matrix one by one as shown in the following code:

```
print(a[0,0])
Output: 5

print(a[0,1])
Output: 6

printa([1,0])
Output: 7

printa([1,1])
Output: 8
```

In the preceding code sample, we have tried to access each element of an array using array indices. You can also understand this by the diagram mentioned here:



In the preceding diagram, we can see it has four blocks and each block represents the element of an array. The values written in each block show its indices.

In this section, we have understood the fundamentals of arrays. Now, let's jump to arrays of numerical data types.

NumPy array numerical data types

Python offers three types of numerical data types: integer type, float type, and complex type. In practice, we need more data types for scientific computing operations with precision, range, and size. NumPy offers a bulk of data types with mathematical types and numbers. Let's see the following table of NumPy numerical types:

Data Type	**Details**
`bool`	This is a Boolean type that stores a bit and takes `True` or `False` values.
`inti`	Platform integers can be either `int32` or `int64`.
`int8`	Byte store values range from `-128` to `127`.
`int16`	This stores integers ranging from `-32768` to `32767`.
`int32`	This stores integers ranging from `-2 ** 31` to `2 ** 31 -1`.
`int64`	This stores integers ranging from `-2 ** 63` to `2 ** 63 -1`.
`uint8`	This stores unsigned integers ranging from `0` to `255`.
`uint16`	This stores unsigned integers ranging from `0` to `65535`.
`uint32`	This stores unsigned integers ranging from `0` to `2 ** 32 – 1`.
`uint64`	This stores unsigned integers ranging from `0` to `2 ** 64 – 1`.

`float16`	Half-precision float; sign bit with 5 bits exponent and 10 bits mantissa.
`float32`	Single-precision float; sign bit with 8 bits exponent and 23 bits mantissa.
`float64` or `float`	Double-precision float; sign bit with 11 bits exponent and 52 bits mantissa.
`complex64`	Complex number stores two 32-bit floats: real and imaginary number.
`complex128` or `complex`	Complex number stores two 64-bit floats: real and imaginary number.

For each data type, there exists a matching conversion function:

```
print(np.float64(21))
Output: 21.0

print(np.int8(21.0))
Output: 42

print(np.bool(21))
Output: True

print(np.bool(0))
Output: False

print(np.bool(21.0))
Output: True

print(np.float(True))
Output: 1.0

print(np.float(False))
Output: 0.0
```

Many functions have a data type argument, which is frequently optional:

```
arr=np.arange(1,11, dtype= np.float32)
print(arr)

Output:
[ 1. 2. 3. 4. 5. 6. 7. 8. 9. 10.]
```

It is important to be aware that you are not allowed to change a complex number into an integer. If you try to convert complex data types into integers, then you will get `TypeError`. Let's see the following example:

```
np.int(42.0 + 1.j)
```

This results in the following output:

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-29-61a3a50e24b1> in <module>
----> 1 np.int(42.0 + 1.j)

TypeError: can't convert complex to int
```

You will get the same error if you try the conversion of a complex number into a floating point.

But you can convert float values into complex numbers by setting individual pieces. You can also pull out the pieces using the `real` and `imag` attributes. Let's see that using the following example:

```
c= complex(42, 1)

print(c) Output:

(42+1j)

print(c.real,c.imag

) Output: 42.0 1.0
```

In the preceding example, you have defined a complex number using the `complex()` method. Also, you have extracted the real and imaginary values using the `real` and `imag` attributes. Let's now jump to `dtype` objects.

dtype objects

We have seen in earlier sections of the chapter that `dtype` tells us the type of individual elements of an array. NumPy array elements have the same data type, which means that all elements have the same `dtype`. `dtype` objects are instances of the `numpy.dtype` class:

```
# Creating an array
import numpy as np a =
np.array([2,4,6,8,10])
```

```
print(a.dtype)
Output: 'int64'
```

`dtype` objects also tell us the size of the data type in bytes using the `itemsize` property:

```
print(a.dtype.itemsize)
Output:8
```

Data type character codes

Character codes are included for backward compatibility with Numeric. Numeric is the predecessor of NumPy. Its use is not recommended, but the code is supplied here because it pops up in various locations. You should use the `dtype` object instead. The following table lists several different data types and the character codes related to them:

Type	Character Code
Integer	i
Unsigned integer	u
Single-precision float	f
Double-precision float	d
Bool	b
Complex	D
String	S
Unicode	U
Void	V

Let's take a look at the following code to produce an array of single-precision floats:

```
# Create numpy array using arange() function
var1=np.arange(1,11, dtype='f')
print(var1)

Output:
[ 1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10.]
```

Likewise, the following code creates an array of complex numbers:

```
print(np.arange(1,6, dtype='D'))

Output:
[1.+0.j, 2.+0.j, 3.+0.j, 4.+0.j, 5.+0.j]
```

dtype constructors

There are lots of ways to create data types using constructors. Constructors are used to instantiate or assign a value to an object. In this section, we will understand data type creation with the help of a floating-point data example: • To try out a general Python float, use the following:

```
print(np.dtype(float))
Output: float64
```

- To try out a single-precision float with a character code, use the following:

```
print(np.dtype('f'))
Output: float32
```

- To try out a double-precision float with a character code, use the following:

```
print(np.dtype('d'))
Output: float64
```

- To try out a `dtype` constructor with a two-character code, use the following:

```
print(np.dtype('f8'))
Output: float64
```

Here, the first character stands for the type and a second character is a number specifying the number of bytes in the type, for example, 2, 4, or 8.

dtype attributes

The `dtype` class offers several useful attributes. For example, we can get information about the character code of a data type using the `dtype` attribute:

```
# Create numpy array
var2=np.array([1,2,3],dtype='float64'

) print(var2.dtype.char) Output: 'd'
```

The `type` attribute corresponds to the type of object of the array elements:

```
print(var2.dtype.type)

Output: <class 'numpy.float64'>
```

Now that we know all about the various data types used in NumPy arrays, let's start manipulating them in the next section.

Manipulating array shapes

In this section, our main focus is on array manipulation. Let's learn some new Python functions of NumPy, such as `reshape()`, `flatten()`, `ravel()`, `transpose()`, and `resize()`:

- `reshape()` will change the shape of the array:

```
#   Create   an   array   arr   =   np.arange(12)
print(arr) Output: [ 0  1  2  3  4  5  6  7  8
9 10 11]

# Reshape the array dimension
new_arr=arr.reshape(4,3)
print(new_arr)

Output: [[ 0,  1,  2],
              [ 3,  4,  5],
              [ 6,  7,  8],
              [ 9, 10, 11]]

# Reshape the array dimension
new_arr2=arr.reshape(3,4)
print(new_arr2)

Output:
array([[ 0,  1,  2,  3],
[ 4,  5,  6,  7],
      [ 8,  9, 10, 11]])
```

- Another operation that can be applied to arrays is `flatten()`. `flatten()` transforms an n-dimensional array into a one-dimensional array:

```
# Create an array
arr=np.arange(1,10).reshape(3,3)
print(arr) Output:
[[1 2 3]
```

```
 [4 5 6]
 [7 8 9]]

print(arr.flatten())

Output:
[1 2 3 4 5 6 7 8 9]
```

- The `ravel()` function is similar to the `flatten()` function. It also transforms an n-dimensional array into a one-dimensional array. The main difference is that `flatten()` returns the actual array while `ravel()` returns the reference of the original array. The `ravel()` function is faster than the `flatten()` function because it does not occupy extra memory:

```
print(arr.ravel())

Output:
[1, 2, 3, 4, 5, 6, 7, 8, 9]
```

- The `transpose()` function is a linear algebraic function that transposes the given two-dimensional matrix. The word transpose means converting rows into columns and columns into rows:

```
# Transpose the matrix
print(arr.transpose())

Output:
[[1 4 7]
[2 5 8]
[3 6 9]]
```

- The `resize()` function changes the size of the NumPy array. It is similar to `reshape()` but it changes the shape of the original array:

```
# resize the matrix
arr.resize(1,9) print(arr)
Output:[[1 2 3 4 5 6 7 8 9]]
```

In all the code in this section, we have seen built-in functions such as `reshape()`, `flatten()`, `ravel()`, `transpose()`, and `resize()` for manipulating size. Now, it's time to learn about the stacking of NumPy arrays.

The stacking of NumPy arrays

NumPy offers a stack of arrays. Stacking means joining the same dimensional arrays along with a new axis. Stacking can be done horizontally, vertically, column-wise, row-wise, or depth-wise:

- **Horizontal stacking**: In horizontal stacking, the same dimensional arrays are joined along with a horizontal axis using the `hstack()` and `concatenate()` functions. Let's see the following example:

```
arr1 = np.arange(1,10).reshape(3,3)
print(arr1)

Output:
[[1 2 3]
 [4 5 6]
 [7 8 9]]
```

We have created one 3*3 array; it's time to create another 3*3 array:

```
arr2 = 2*arr1
print(arr2)

Output:
[[ 2 4 6]
 [ 8 10 12]
 [14 16 18]]
```

After creating two arrays, we will perform horizontal stacking:

```
# Horizontal Stacking
arr3=np.hstack((arr1, arr2))
print(arr3)

Output:
[[ 1 2 3 2 4 6]
 [ 4 5 6 8 10 12]
 [ 7 8 9 14 16 18]]
```

In the preceding code, two arrays are stacked horizontally along the *x* axis. The `concatenate()` function can also be used to generate the horizontal stacking with axis parameter value `1`:

```
# Horizontal stacking using concatenate() function
arr4=np.concatenate((arr1, arr2), axis=1)
print(arr4)
Output:
[[ 1 2 3 2 4 6]
```

```
 [ 4  5  6  8 10 12]
 [ 7  8  9 14 16 18]]
```

In the preceding code, two arrays have been stacked horizontally using the `concatenate()` function.

- **Vertical stacking**: In vertical stacking, the same dimensional arrays are joined along with a vertical axis using the `vstack()` and `concatenate()` functions. Let's see the following example:

```
# Vertical stacking
arr5=np.vstack((arr1, arr2))
print(arr5)

Output:
[[ 1  2  3]
 [ 4  5  6]
 [ 7  8  9]
 [ 2  4  6]
 [ 8 10 12]
 [14 16 18]]
```

In the preceding code, two arrays are stacked vertically along the *y* axis. The `concatenate()` function can also be used to generate vertical stacking with axis parameter value `0`:

```
arr6=np.concatenate((arr1, arr2), axis=0)
print(arr6)

Output:
[[ 1  2  3]
 [ 4  5  6]
 [ 7  8  9]
 [ 2  4  6]
 [ 8 10 12]
 [14 16 18]]
```

In the preceding code, two arrays are stacked vertically using the `concatenate()` function.

- **Depth stacking**: In depth stacking, the same dimensional arrays are joined along with a third axis (depth) using the `dstack()` function. Let's see the following example:

```
arr7=np.dstack((arr1, arr2))
print(arr7)
```

```
Output:
[[[ 1  2]
  [ 2  4]
  [ 3  6]]

 [[ 4  8]
  [ 5 10]
  [ 6 12]]

 [[ 7 14]
  [ 8 16]
  [ 9 18]]]
```

In the preceding code, two arrays are stacked in depth along with a third axis (depth).

- **Column stacking**: Column stacking stacks multiple sequence one-dimensional arrays as columns into a single two-dimensional array. Let's see an example of column stacking:

```
# Create 1-D array
arr1 = np.arange(4,7)
print(arr1) Output:
[4, 5, 6]
```

In the preceding code block, we have created a one-dimensional NumPy array.

```
# Create 1-D array
arr2 = 2 * arr1
print(arr2) Output:
[ 8, 10, 12]
```

In the preceding code block, we have created another one-dimensional NumPy array.

```
# Create column stack
arr_col_stack=np.column_stack((arr1,arr2))
print(arr_col_stack)
Output:
[[ 4  8]
 [ 5 10]
 [ 6 12]]
```

In the preceding code, we have created two one-dimensional arrays and stacked them column-wise.

- **Row stacking**: Row stacking stacks multiple sequence one-dimensional arrays as rows into a single two-dimensional arrays. Let's see an example of row stacking:

```
# Create row stack
arr_row_stack = np.row_stack((arr1,arr2))
print(arr_row_stack)

Output:
[[ 4 5 6]
 [ 8 10 12]]
```

In the preceding code, two one-dimensional arrays are stacked row-wise.

Let's now see how to partition a NumPy array into multiple sub-arrays.

Partitioning NumPy arrays

NumPy arrays can be partitioned into multiple sub-arrays. NumPy offers three types of split functionality: vertical, horizontal, and depth-wise. All the split functions by default split into the same size arrays but we can also specify the split location. Let's look at each of the functions in detail:

- **Horizontal splitting**: In horizontal split, the given array is divided into *N* equal sub-arrays along the horizontal axis using the `hsplit()` function. Let's see how to split an array:

```
# Create an array
arr=np.arange(1,10).reshape(3,3)
print(arr)

Output:
[[1 2 3]
 [4 5 6]
 [7 8 9]]

# Peroform horizontal splitting
arr_hor_split=np.hsplit(arr, 3) print(arr_hor_split)

Output:
[array([[1],
```

```
        [4],
        [7]]), array([[2],
        [5],
        [8]]), array([[3],
        [6],
        [9]])]
```

In the preceding code, the `hsplit(arr, 3)` function divides the array into three sub-arrays. Each part is a column of the original array.

- **Vertical splitting**: In vertical split, the given array is divided into *N* equal subarrays along the vertical axis using the `vsplit()` and `split()` functions. The `split` function with `axis=0` performs the same operation as the `vsplit()` function:

```
# vertical split
arr_ver_split=np.vsplit(arr, 3)
print(arr_ver_split)
```

```
Output:
[array([[1, 2, 3]]), array([[4, 5, 6]]), array([[7, 8, 9]])]
```

In the preceding code, the `vsplit(arr, 3)` function divides the array into three sub-arrays. Each part is a row of the original array. Let's see another function, `split()`, which can be utilized as a vertical and horizontal split, in the following example:

```
# split with axis=0
arr_split=np.split(arr,3,axis=0)
print(arr_split)
```

```
Output:
[array([[1, 2, 3]]), array([[4, 5, 6]]), array([[7, 8, 9]])]
```

```
# split with axis=1 arr_split =
np.split(arr,3,axis=1)
```

```
Output:
[array([[1],
        [4],
        [7]]), array([[2],
        [5],
        [8]]), array([[3],
        [6],
```

```
[9]]])]
```

In the preceding code, the `split(arr, 3)` function divides the array into three sub-arrays. Each part is a row of the original array. The split output is similar to the `vsplit()` function when `axis=0` and the split output is similar to the `hsplit()` function when `axis=1`.

Changing the data type of NumPy arrays

As we have seen in the preceding sections, NumPy supports multiple data types, such as `int`, `float`, and complex numbers. The `astype()` function converts the data type of the array. Let's see an example of the `astype()` function:

```
# Create an array
arr=np.arange(1,10).reshape(3,3)
print("Integer Array:",arr)

# Change datatype of array
arr=arr.astype(float)

# print array
print("Float Array:",
arr)

# Check new data type of array
print("Changed Datatype:", arr.dtype)
```

In the preceding code, we have created one NumPy array and checked its data type using the `dtype` attribute.

Let's change the data type of an array using the `astype()` function:

```
# Change datatype of array
arr=arr.astype(float)

# Check new data type of array
print(arr.dtype)

Output:
float64
```

In the preceding code, we have changed the column data type from integer to float using `astype()`.

The `tolist()` function converts a NumPy array into a Python list. Let's see an example of the `tolist()` function:

```
# Create an array
arr=np.arange(1,10)

# Convert NumPy array to Python List
list1=arr.tolist()
print(list1)

Output:
[1, 2, 3, 4, 5, 6, 7, 8, 9]
```

In the preceding code, we have converted an array into a Python list object using the `tolist()` function.

Creating NumPy views and copies

Some of the Python functions return either a copy or a view of the input array. A Python copy stores the array in another location while a view uses the same memory content. This means copies are separate objects and treated as a deep copy in Python. Views are the original base array and are treated as a shallow copy. Here are some properties of copies and views:

- Modifications in a view affect the original data whereas modifications in a copy do not affect the original array.
- Views use the concept of shared memory.
- Copies require extra space compared to views.
- Copies are slower than views.

Let's understand the concept of copy and view using the following example:

```
# Create NumPy Array arr =
np.arange(1,5).reshape(2,2)
print(arr)

Output:
[[1, 2],
[3, 4]]
```

After creating a NumPy array, let's perform object copy operations:

```
# Create no copy only assignment
arr_no_copy=arr
```

```
# Create Deep Copy
arr_copy=arr.copy()

# Create shallow copy using View
arr_view=arr.view()

print("Original Array: ",id(arr))
print("Assignment: ",id(arr_no_copy))
print("Deep Copy: ",id(arr_copy))
print("Shallow Copy(View): ",id(arr_view))
```

```
Output:
Original Array:  140426327484256
Assignment:  140426327484256
Deep Copy:  140426327483856
Shallow Copy(View):  140426327484496
```

In the preceding example, you can see the original array and the assigned array have the same object ID, meaning both are pointing to the same object. Copies and views both have different object IDs; both will have different objects, but view objects will reference the same original array and a copy will have a different replica of the object.

Let's continue with this example and update the values of the original array and check its impact on views and copies:

```
# Update the values of original array
arr[1]=[99,89]

# Check values of array view
print("View Array:\n", arr_view)

# Check values of array copy
print("Copied Array:\n", arr_copy)
```

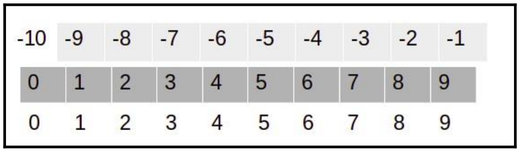
```
Output:
View Array:
 [[ 1  2]
 [99 89]]
Copied Array:
 [[1 2]
 [3 4]]
```

In the preceding example, we can conclude from the results that the view is the original array. The values changed when we updated the original array and the copy is a separate object because its values remain the same.

Slicing NumPy arrays

Slicing in NumPy is similar to Python lists. Indexing prefers to select a single value while slicing is used to select multiple values from an array.

NumPy arrays also support negative indexing and slicing. Here, the negative sign indicates the opposite direction and indexing starts from the right-hand side with a starting value of `-1`:



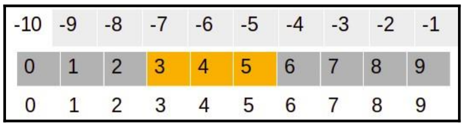
Let's check this out using the following code:

```
# Create NumPy Array arr =
np.arange(0,10) print(arr) Output:
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

In the slice operation, we use the colon symbol to select the collection of values. Slicing takes three values: start, stop, and step:

```
print(arr[3:6])
Output: [3, 4, 5]
```

This can be represented as follows:



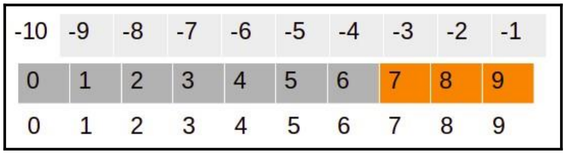
In the preceding example, we have used `3` as the starting index and `6` as the stopping index:

```
print(arr[3:]) Output: array([3, 4,
5, 6, 7, 8, 9])
```

In the preceding example, only the starting index is given. `3` is the starting index. This slice operation will select the values from the starting index to the end of the array:

```
print(arr[-3:]) Output:
array([7, 8, 9])
```

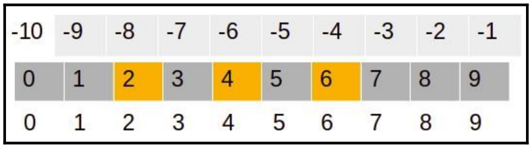
This can be represented as follows:



In the preceding example, the slice operation will select values from the third value from the right side of the array to the end of the array:

```
print(arr[2:7:2])
Output: array([2, 4,6])
```

This can be represented as follows:



In the preceding example, the start, stop, and step index are 2, 7, and 2, respectively. Here, the slice operation selects values from the second index to the sixth (one less than the stop value) index with an increment of 2 in the index value. So, the output will be 2, 4, and 6.

Boolean and fancy indexing

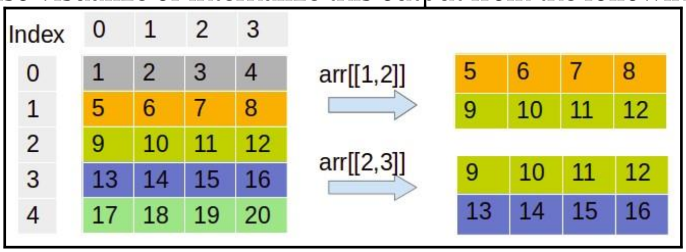
Indexing techniques help us to select and filter elements from a NumPy array. In this section, we will focus on Boolean and fancy indexing. Boolean indexing uses a Boolean expression in the place of indexes (in square brackets) to filter the NumPy array. This indexing returns elements that have a true value for the Boolean expression:

```
# Create NumPy Array arr =
np.arange(21,41,2)
print("Orignial
Array:\n",arr)

# Boolean Indexing print("After Boolean
Condition:",arr[arr>30])

Output:
Orignial Array:
 [21 23 25 27 29 31 33 35 37 39]
After Boolean Condition: [31 33 35 37 39]
```

Fancy indexing is a special type of indexing in which elements of an array are selected by an array of indices. This means we pass the array of indices in brackets. Fancy indexing also supports multi-dimensional arrays. This will help us to easily select and modify a complex multi-dimensional set of arrays. Let's see an example as follows to understand fancy indexing:

```
# Create NumPy Array
arr = np.arange(1,21).reshape(5,4)
print("Orignial Array:\n",arr)

# Selecting 2nd and 3rd row
indices = [1,2]
print("Selected 1st and 2nd Row:\n", arr[indices])

# Selecting 3nd and 4th row
indices = [2,3] print("Selected 3rd and 4th

Row:\n", arr[indices]) Output:

Orignial Array:
 [[ 1 2 3 4]
 [ 5 6 7 8]
 [ 9 10 11 12]
 [13 14 15 16]
 [17 18 19 20]] Selected
1st and 2nd Row:
 [[ 5 6 7 8]
 [ 9 10 11 12]] Selected
3rd and 4th Row:
 [[ 9 10 11 12]
 [13 14 15 16]]
```

In the preceding code, we have created a 5*4 matrix and selected the rows using integer indices. You can also visualize or internalize this output from the following diagram:



We can see the code for this as follows:

```
# Create row and column indices row =
np.array([1, 2]) col = np.array([2, 3])
```

```
print("Selected Sub-Array:", arr[row,
col])
```

Output:

```
Selected Sub-Array: [ 7 12]
```

The preceding example results in the first value, `[1,2]`, and second value, `[2,3]`, as the row and column index. The array will select the value at the first and second index values, which are 7 and 12.

Broadcasting arrays

Python lists do not support direct vectorizing arithmetic operations. NumPy offers a fastervectorized array operation compared to Python list loop-based operations. Here, all the looping operations are performed in C instead of Python, which makes it faster. Broadcasting functionality checks a set of rules for applying binary functions, such as addition, subtraction, and multiplication, on different shapes of an array.

Let's see an example of broadcasting:

```
# Create NumPy Array
arr1 = np.arange(1,5).reshape(2,2)
print(arr1)
```

Output:

```
[[1 2]
 [3 4]]
```

```
# Create another NumPy Array arr2
= np.arange(5,9).reshape(2,2)
print(arr2)
```

Output:

```
[[5 6]
 [7 8]]
```

```
# Add two matrices
print(arr1+arr2)
```

Output:

```
[[ 6 8]
 [10 12]]
```

In all three preceding examples, we can see the addition of two arrays of the same size. This concept is known as broadcasting:

```
# Multiply two matrices
print(arr1*arr2)

Output:
[[ 5 12]
 [21 32]]
```

In the preceding example, two matrices were multiplied. Let's perform addition and multiplication with a scalar value:

```
# Add a scaler value
print(arr1 + 3)

Output:
[[4 5]
 [6 7]]

# Multiply with a scalar value
print(arr1 * 3)
Output:
[[ 3 6]
 [ 9 12]]
```

In the preceding two examples, the matrix is added and multiplied by a scalar value.

Creating pandas DataFrames

The `pandas` library is designed to work with a panel or tabular data. `pandas` is a fast, highly efficient, and productive tool for manipulating and analyzing string, numeric, datetime, and time-series data. `pandas` provides data structures such as DataFrames and Series. A `pandas` DataFrame is a tabular, two-dimensional labeled and indexed data structure with a grid of rows and columns. Its columns are heterogeneous types. It has the capability to work with different types of objects, carry out grouping and joining operations, handle missing values, create pivot tables, and deal with dates. A `pandas` DataFrame can be created in multiple ways. Let's create an empty DataFrame:

```
# Import pandas library
import pandas as pd
```

```
# Create empty DataFrame
df = pd.DataFrame()

# Header of dataframe.
df.head()
```

Output:

```
_
```

In the preceding example, we have created an empty DataFrame. Let's create a DataFrame using a dictionary of the list:

```
# Create dictionary of list
data = {'Name': ['Vijay', 'Sundar', 'Satyam', 'Indira'], 'Age': [23, 45,
46, 52 ]}

# Create the pandas DataFrame
df = pd.DataFrame(data)

# Header of dataframe.
df.head()
```

Output:

```
  Name Age
0 Vijay 23
1 Sundar 45
2 Satyam 46
3 Indira 52
```

In the preceding code, we have used a dictionary of the list to create a DataFrame. Here, the keys of the dictionary are equivalent to columns, and values are represented as a list that is equivalent to the rows of the DataFrame. Let's create a DataFrame using the list of dictionaries:

```
# Pandas DataFrame by lists of dicts.
# Initialise data to lists. data =[ {'Name': 'Vijay', 'Age': 23},{'Name':
'Sundar', 'Age': 25},{'Name': 'Shankar', 'Age': 26}]

# Creates DataFrame. df =
pd.DataFrame(data,columns=['Name','Age'])

# Print dataframe header
df.head()
```

In the preceding code, the DataFrame is created using a list of dictionaries. In the list, each item is a dictionary. Each key is the name of the column and the value is the cell value for a row. Let's create a DataFrame using a list of tuples:

```
# Creating DataFrame using list of tuples. data = [('Vijay', 23),(
'Sundar', 45), ('Satyam', 46), ('Indira',52)]

# Create dataframe
df = pd.DataFrame(data, columns=['Name','Age'])

# Print dataframe header
df.head()

Output:
  Name Age
0 Vijay 23
1 Sundar 25
2 Shankar 26
```

In the preceding code, the DataFrame is created using a list of tuples. In the list, each item is a tuple and each tuple is equivalent to the row of columns.

Understanding pandas Series

`pandas` Series is a one-dimensional sequential data structure that is able to handle any type of data, such as string, numeric, datetime, Python lists, and dictionaries with labels and indexes. Series is one of the columns of a DataFrame. We can create a Series using a Python dictionary, NumPy array, and scalar value. We will also see the `pandas` Series features and properties in the latter part of the section. Let's create some Python Series:

- **Using a Python dictionary**: Create a dictionary object and pass it to the Series object. Let's see the following example:

```
# Creating Pandas Series using Dictionary
dict1 = {0 : 'Ajay', 1 : 'Jay', 2 : 'Vijay'}

# Create Pandas Series
series = pd.Series(dict1)

# Show series
series

Output:
```

```
0     Ajay
1      Jay

2    Vijay

dtype: object
```

- **Using a NumPy array**: Create a NumPy array object and pass it to the Series object. Let's see the following example:

```
#Load Pandas and NumPy libraries
import pandas as pd
import numpy as np

# Create NumPy array arr =
np.array([51,65,48,59, 68])

# Create Pandas Series
series = pd.Series(arr)
series Output:
0    51
1    65
2    48
3    59

4    68

dtype: int64
```

- **Using a single scalar value**: To create a `pandas` Series with a scalar value, pass the scalar value and index list to a Series object:

```
# load Pandas and NumPy
import pandas as pd
import numpy as np

# Create Pandas Series
series = pd.Series(10, index=[0, 1, 2, 3, 4, 5])
series

Output:
0                                                                 45
1                                                                 45
2                                                                 45
3                                                                 45
```

```
4                                                    45
5dtype: int64                                        45
```

Let's explore some features of pandas Series:

- We can also create a series by selecting a column, such as country, which happens to be the first column in the datafile. Then, show the type of the object currently in the local scope:

```
# Import pandas
import pandas as pd

# Load data using read_csv() df =
pd.read_csv("WHO_first9cols.csv")

# Show initial 5 records
df.head()
```

This results in the following output:

	Country	CountryID	Continent	Adolescent fertility rate (%)	Adult literacy rate (%)	Gross national income per capita (PPP international $)	Net primary school enrolment ratio female (%)	Net primary school enrolment ratio male (%)	Population (in thousands) total
0	Afghanistan	1	1	151.0	28.0	NaN	NaN	NaN	26088.0
1	Albania	2	2	27.0	98.7	6000.0	93.0	94.0	3172.0
2	Algeria	3	3	6.0	69.9	5940.0	94.0	96.0	33351.0
3	Andorra	4	2	NaN	NaN	NaN	83.0	83.0	74.0
4	Angola	5	3	146.0	67.4	3890.0	49.0	51.0	16557.0

In the output, you can see the top five records in the WHO_first9cols dataset using the head() function:

```
# Select a series
country_series=df['Country']

# check datatype of series
type(country_series)

Output:
pandas.core.series.Series
```

- The pandas Series data structure shares some of the common attributes of DataFrames and also has a name attribute. Explore these properties as follows:

```
# Show the shape of DataFrame
print("Shape:", df.shape)
```

```
Output:
Shape: (202, 9)
```

Let's check the column list of a DataFrame:

```
# Check the column list of DataFrame
print("List of Columns:", df.columns)

Output:List of Columns: Index(['Country', 'CountryID', 'Continent',
'Adolescent fertility rate (%)',
       'Adult literacy rate (%)',
       'Gross national income per capita (PPP international $)',
       'Net primary school enrolment ratio female (%)',
       'Net primary school enrolment ratio male (%)',
       'Population (in thousands) total'],
dtype='object')
```

Let's check the data types of DataFrame columns:

```
# Show the datatypes of columns
print("Data types:", df.dtypes)

Output:
Data types: Country
object
            CountryID
int64
            Continent
int64
            Adolescent fertility rate (%)
float64
            Adult literacy rate (%)
float64
            Gross national income per capita (PPP international $)
float64
            Net primary school enrolment ratio female (%)
float64
            Net primary school enrolment ratio male (%)
float64
            Population (in thousands) total
float64
            dtype: object
```

3. Let's see the slicing of a `pandas` Series:

```
# Pandas Series Slicing country_series[-
5:]
```

```
Output:
197                 Vietnam
198                 West Bank and Gaza
199                 Yemen
200                 Zambia
201                 Zimbabwe
Name: Country, dtype: object
```

Now that we know how to use pandas Series, let's move on to using Quandl to work on databases.

Reading and querying the Quandl data

In the last section, we saw `pandas` DataFrames that have a tabular structure similar to relational databases. They offer similar query operations on DataFrames. In this section, we will focus on Quandl. Quandl is a Canada-based company that offers commercial and alternative financial data for investment data analyst. Quandl understands the need for investment and financial quantitative analysts. It provides data using API, R, Python, or Excel.

In this section, we will retrieve the Sunspot dataset from Quandl. We can use either an API or download the data manually in CSV format.

Let's first install the Quandl package using `pip`:

```
$ pip3 install Quandl
```

If you want to install the API, you can do so by downloading installers from `https:// pypi. python.org/ pypi/ Quandl` or by running the preceding command.

> Using the API is free, but is limited to 50 API calls per day. If you require more API calls, you will have to request an authentication key. The code in this tutorial does not use a key. It should be simple to change the code to either use a key or read a downloaded CSV file. If you have difficulties, refer to the *Where to find help and references* section in `Chapter 1`, *Getting Started with Python Libraries*, or search through the Python docs at `https:/ /docs. python. org/ 2 /`.

Let's take a look at how to query data in a `pandas` DataFrame:

1. As a first step, we obviously have to download the data. After importing the Quandl API, get the data as follows:

   ```
   import quandl
   ```

```
sunspots = quandl.get("SIDC/SUNSPOTS_A")
```

2. The `head()` and `tail()` methods have a purpose similar to that of the Unix commands with the same name. Select the first *n* and last *n* records of a DataFrame, where *n* is an integer parameter:

```
sunspots.head()
```

This results in the following output:

Date	Yearly Mean Total Sunspot Number	Yearly Mean Standard Deviation	Number of Observations	Definitive/Provisional Indicator
1700-12-31	8.3	NaN	NaN	1.0
1701-12-31	18.3	NaN	NaN	1.0
1702-12-31	26.7	NaN	NaN	1.0
1703-12-31	38.3	NaN	NaN	1.0
1704-12-31	60.0	NaN	NaN	1.0

Let's check out the `tail` function as follows:

```
sunspots.tail()
```

This results in the following output:

Date	Yearly Mean Total Sunspot Number	Yearly Mean Standard Deviation	Number of Observations	Definitive/Provisional Indicator
2015-12-31	69.8	6.4	8903.0	1.0
2016-12-31	39.8	3.9	9940.0	1.0
2017-12-31	21.7	2.5	11444.0	1.0
2018-12-31	7.0	1.1	12611.0	1.0
2019-12-31	3.6	0.5	12401.0	0.0

The `head()` and `tail()` methods give us the first and last five rows of the Sunspot data, respectively.

3. **Filtering columns**: `pandas` offers the ability to select columns. Let's select columns in a `pandas` DataFrame:

```
# Select columns
sunspots_filtered=sunspots[['Yearly Mean Total Sunspot
Number','Definitive/Provisional Indicator']]

# Show top 5 records
sunspots_filtered.head()
```

This results in the following output:

Date	Yearly Mean Total Sunspot Number	Definitive/Provisional Indicator
1700-12-31	8.3	1.0
1701-12-31	18.3	1.0
1702-12-31	26.7	1.0
1703-12-31	38.3	1.0
1704-12-31	60.0	1.0

4. **Filtering rows**: `pandas` offers the ability to select rows. Let's select rows in a `pandas` DataFrame:

```
# Select rows using index
sunspots["20020101": "20131231"]
```

This results in the following output:

Date	Yearly Mean Total Sunspot Number	Yearly Mean Standard Deviation	Number of Observations	Definitive/Provisional Indicator
2002-12-31	163.6	9.8	6588.0	1.0
2003-12-31	99.3	7.1	7087.0	1.0
2004-12-31	65.3	5.9	6882.0	1.0
2005-12-31	45.8	4.7	7084.0	1.0
2006-12-31	24.7	3.5	6370.0	1.0
2007-12-31	12.6	2.7	6841.0	1.0
2008-12-31	4.2	2.5	6644.0	1.0
2009-12-31	4.8	2.5	6465.0	1.0
2010-12-31	24.9	3.4	6328.0	1.0
2011-12-31	80.8	6.7	6077.0	1.0
2012-12-31	84.5	6.7	5753.0	1.0
2013-12-31	94.0	6.9	5347.0	1.0

5. **Boolean filtering**: We can query data using Boolean conditions similar to the `WHERE` clause condition of SQL. Let's filter the data greater than the arithmetic mean:

```
# Boolean Filter
sunspots[sunspots['Yearly Mean Total Sunspot Number'] >
sunspots['Yearly Mean Total Sunspot Number'].mean()]
```

This results in the following output:

Date	Yearly Mean Total Sunspot Number	Yearly Mean Standard Deviation	Number of Observations	Definitive/Provisional Indicator
1705-12-31	96.7	NaN	NaN	1.0
1717-12-31	105.0	NaN	NaN	1.0
1718-12-31	100.0	NaN	NaN	1.0
1726-12-31	130.0	NaN	NaN	1.0
1727-12-31	203.3	NaN	NaN	1.0
1728-12-31	171.7	NaN	NaN	1.0
1729-12-31	121.7	NaN	NaN	1.0
1736-12-31	116.7	NaN	NaN	1.0
1737-12-31	135.0	NaN	NaN	1.0
1738-12-31	185.0	NaN	NaN	1.0
1739-12-31	168.3	NaN	NaN	1.0
1740-12-31	121.7	NaN	NaN	1.0

Describing pandas DataFrames

The `pandas` DataFrame has a dozen statistical methods. The following table lists these methods, along with a short description of each:

Method	Description
`describes`	This method returns a small table with descriptive statistics.
`count`	This method returns the number of non-NaN items.
`mad`	This method calculates the mean absolute deviation, which is a robust measure similar to standard deviation.
`median`	This method returns the median. This is equivalent to the value at the 50^{th} percentile.
`min`	This method returns the minimum value.
`max`	This method returns the maximum value.
`mode`	This method returns the mode, which is the most frequently occurring value.
`std`	This method returns the standard deviation, which measures dispersion. It is the square root of the variance.

`var`	This method returns the variance.
`skew`	This method returns skewness. Skewness is indicative of the distribution symmetry.
`kurt`	This method returns kurtosis. Kurtosis is indicative of the distribution shape.

Using the same data used in the previous section, we will demonstrate these statistical methods:

```
# Describe the dataset
df.describe()
```

This results in the following output:

	CountryID	Continent	Adolescent fertility rate (%)	Adult literacy rate (%)	Gross national income per capita (PPP international $)	Net primary school enrolment ratio female (%)	Net primary school enrolment ratio male (%)	Population (in thousands) total
count	202.000000	202.000000	177.000000	131.000000	178.000000	179.000000	179.000000	1.890000e+02
mean	101.500000	3.579208	59.457627	78.871756	11250.112360	84.033520	85.698324	3.409964e+04
std	58.456537	1.808263	49.105286	20.415760	12586.753417	17.788047	15.451212	1.318377e+05
min	1.000000	1.000000	0.000000	23.600000	260.000000	6.000000	11.000000	2.000000e+00
25%	51.250000	2.000000	19.000000	68.400000	2112.500000	79.000000	79.500000	1.328000e+03
50%	101.500000	3.000000	46.000000	86.500000	6175.000000	90.000000	90.000000	6.640000e+03
75%	151.750000	5.000000	91.000000	95.300000	14502.500000	96.000000	96.000000	2.097100e+04
max	202.000000	7.000000	199.000000	99.800000	60870.000000	100.000000	100.000000	1.328474e+06

The `describe()` method will show most of the descriptive statistical measures for all columns:

```
# Count number of observation
df.count()
```

This results in the following output:

```
Country                                             202
CountryID                                           202
Continent                                           202
Adolescent fertility rate (%)                       177
Adult literacy rate (%)                             131
Gross national income per capita (PPP international $)    178
Net primary school enrolment ratio female (%)       179
Net primary school enrolment ratio male (%)         179
Population (in thousands) total                     189
dtype: int64
```

The `count()` method counts the number of observations in each column. It helps us to check the missing values in the dataset. Except for the initial three columns, all the columns have missing values. Similarly, you can compute the median, standard deviation, mean absolute deviation, variance, skewness, and kurtosis:

```
# Compute median of all the columns
df.median()
```

This results in the following output:

```
CountryID                                                   101.5
Continent                                                     3.0
Adolescent fertility rate (%)                                46.0
Adult literacy rate (%)                                      86.5
Gross national income per capita (PPP international $)     6175.0
Net primary school enrolment ratio female (%)                90.0
Net primary school enrolment ratio male (%)                  90.0
Population (in thousands) total                            6640.0
dtype: float64
```

We can compute deviation for all columns as follows:

```
# Compute the standard deviation of all the columns
df.std()
```

This results in the following output:

```
CountryID                                                     58.456537
Continent                                                      1.808263
Adolescent fertility rate (%)                                 49.105286
Adult literacy rate (%)                                       20.415760
Gross national income per capita (PPP international $)     12586.753417
Net primary school enrolment ratio female (%)                 17.788047
Net primary school enrolment ratio male (%)                   15.451212
Population (in thousands) total                           131837.708677
dtype: float64
```

The preceding code example is computing the standard deviation for each numeric column.

Grouping and joining pandas DataFrame

Grouping is a kind of data aggregation operation. The grouping term is taken from a relational database. Relational database software uses the `group by` keyword to group similar kinds of values in a column. We can apply aggregate functions on groups such as mean, min, max, count, and sum. The `pandas` DataFrame also offers similar kinds of capabilities. Grouping operations are based on the split-apply-combine strategy. It first divides data into groups and applies the aggregate operation, such as mean, min, max, count, and sum, on each group and combines results from each group:

```
# Group By DataFrame on the basis of Continent column
df.groupby('Continent').mean()
```

This results in the following output:

Continent	CountryID	Adolescent fertility rate (%)	Adult literacy rate (%)	Gross national income per capita (PPP international $)	Net primary school enrolment ratio female (%)	Net primary school enrolment ratio male (%)	Population (in thousands) total
1	110.238095	37.300000	76.900000	14893.529412	85.789474	88.315789	16843.350000
2	100.333333	20.500000	97.911538	19777.083333	92.911111	93.088889	17259.627451
3	99.354167	111.644444	61.690476	3050.434783	67.574468	72.021277	16503.195652
4	56.285714	49.600000	91.600000	24524.000000	95.000000	94.400000	73577.333333
5	94.774194	77.888889	87.940909	7397.142857	89.137931	88.517241	15637.241379
6	121.228571	39.260870	87.607143	12167.200000	89.040000	89.960000	25517.142857
7	80.777778	57.333333	69.812500	2865.555556	85.444444	88.888889	317683.666667

Let's now group the DataFrames based on literacy rates as well:

```
# Group By DataFrame on the basis of continent and select adult literacy
rate(%) df.groupby('Continent').mean()['Adult literacy
rate (%)']
```

This results in the following output:

```
Continent
1    76.900000
2    97.911538
3    61.690476
4    91.600000
5    87.940909
6    87.607143
7    69.812500
Name: Adult literacy rate (%), dtype: float64
```

In the preceding example, the continent-wise average adult literacy rate in percentage was computed. You can also group based on multiple columns by passing a list of columns to the `groupby()` function.

Join is a kind of merge operation for tabular databases. The join concept is taken from the relational database. In relational databases, tables were normalized or broken down to reduce redundancy and inconsistency, and join is used to select the information from multiple tables. A data analyst needs to combine data from multiple sources. `pandas` also offers to join functionality to join multiple DataFrames using the `merge()` function.

To understand joining, we will take a taxi company use case. We are using two files: `dest.csv` and `tips.csv`. Every time a driver drops any passenger at their destination, we will insert a record (employee number and destination) into the `dest.csv` file. Whenever drivers get a tip, we insert the record (employee number and tip amount) into the `tips.csv` file. You can download both the files from the following

```
# Import pandas
import pandas as pd

# Load data using read_csv()
dest = pd.read_csv("dest.csv")

# Show DataFrame
dest.head()
```

This results in the following output:

	EmpNr	Dest
0	5	The Hague
1	3	Amsterdam
2	9	Rotterdam

In the preceding code block, we have read the `dest.csv` file using the `read_csv()` method:

```
# Load data using read_csv()
tips = pd.read_csv("tips.csv")

# Show DataFrame
tips.head()
```

This results in the following output:

	EmpNr	Amount
0	5	10.0
1	9	5.0
2	7	2.5

In the preceding code block, we have read the `tips.csv` file using the `read_csv()` method. We will now check out the various types of joins as follows:

- **Inner join**: Inner join is equivalent to the intersection operation of a set. It will select only common records in both the DataFrames. To perform inner join, use the `merge()` function with both the DataFrames and common attribute on the parameter and inner value to show the parameter. The `on` parameter is used to provide the common attribute based on the join will be performed and `how` defines the type of join:

```
# Join DataFrames using Inner Join
df_inner= pd.merge(dest, tips, on='EmpNr', how='inner')
df_inner.head()
```

This results in the following output:

	EmpNr	Dest	Amount
0	5	The Hague	10.0
1	9	Rotterdam	5.0

- **Full outer join**: Outer join is equivalent to a union operation of the set. It merges the right and left DataFrames. It will have all the records from both DataFrames and fills NaNs where the match will not be found:

```
# Join DataFrames using Outer Join
df_outer= pd.merge(dest, tips, on='EmpNr', how='outer')
df_outer.head()
```

This results in the following output:

	EmpNr	Dest	Amount
0	5	The Hague	10.0
1	3	Amsterdam	NaN
2	9	Rotterdam	5.0
3	7	NaN	2.5

- **Right outer join**: In the right outer join, all the records from the right side of the DataFrame will be selected. If the matched records cannot be found in the left DataFrame, then it is filled with NaNs:

```
# Join DataFrames using Right Outer Join df_right=
pd.merge(dest, tips, on='EmpNr', how='right')
df_right.head()
```

This results in the following output:

	EmpNr	Dest	Amount
0	5	The Hague	10.0
1	9	Rotterdam	5.0
2	7	NaN	2.5

- **Left outer join**: In the left outer join, all the records from the left side of the DataFrame will be selected. If the matched records cannot be found in the right DataFrame, then it is filled with NaNs:

```
# Join DataFrames using Left Outer Join
df_left= pd.merge(dest, tips, on='EmpNr', how='left')
df_left.head()
```

This results in the following output:

	EmpNr	Dest	Amount
0	5	The Hague	10.0
1	3	Amsterdam	NaN
2	9	Rotterdam	5.0

We will now move on to checking out missing values in the datasets.

Working with missing values

Most real-world datasets are messy and noisy. Due to their messiness and noise, lots of values are either faulty or missing. `pandas` offers lots of built-in functions to deal with missing values in DataFrames:

- **Check missing values in a DataFrame**: `pandas`' `isnull()` function checks for the existence of null values and returns `True` or `False`, where `True` is for null and `False` is for not-null values. The `sum()` function will sum all the `True` values and returns the count of missing values. We have tried two ways to count the missing values; both show the same output:

```
# Count missing values in DataFrame
pd.isnull(df).sum()
```

The following is the second method:

```
df.isnull().sum()
```

This results in the following output:

```
Country                                                0
CountryID                                              0
Continent                                              0
Adolescent fertility rate (%)                         25
Adult literacy rate (%)                               71
Gross national income per capita (PPP international $)   24
Net primary school enrolment ratio female (%)         23
Net primary school enrolment ratio male (%)           23
Population (in thousands) total                       13
dtype: int64
```

- **Drop missing values**: A very naive approach to deal with missing values is to drop them for analysis purposes. `pandas` has the `dropna()` function to drop or delete such observations from the DataFrame. Here, the `inplace=True` attribute makes the changes in the original DataFrame:

```
# Drop all the missing values
df.dropna(inplace=True)
df.info()
```

This results in the following output:

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 118 entries, 1 to 200
Data columns (total 9 columns):
Country                                                  118 non-null object
CountryID                                                118 non-null int64
Continent                                                118 non-null int64
Adolescent fertility rate (%)                            118 non-null float64
Adult literacy rate (%)                                  118 non-null float64
Gross national income per capita (PPP international $)   118 non-null float64
Net primary school enrolment ratio female (%)            118 non-null float64
Net primary school enrolment ratio male (%)              118 non-null float64
Population (in thousands) total                          118 non-null float64
dtypes: float64(6), int64(2), object(1)
memory usage: 9.2+ KB
```

Here, the number of observations is reduced to 118 from 202.

- **Fill the missing values**: Another approach is to fill the missing values with zero, mean, median, or constant values:

```
# Fill missing values with 0
df.fillna(0,inplace=True)
df.info()
```

This results in the following output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 202 entries, 0 to 201
Data columns (total 9 columns):
Country                                                    202 non-null object
CountryID                                                  202 non-null int64
Continent                                                  202 non-null int64
Adolescent fertility rate (%)                              202 non-null float64
Adult literacy rate (%)                                    202 non-null float64
Gross national income per capita (PPP international $)     202 non-null float64
Net primary school enrolment ratio female (%)              202 non-null float64
Net primary school enrolment ratio male (%)                202 non-null float64
Population (in thousands) total                            202 non-null float64
dtypes: float64(6), int64(2), object(1)
memory usage: 14.3+ KB
```

Here, we have filled the missing values with 0. This is all about handling missing values.

In the next section, we will focus on pivot tables.

Creating pivot tables

A pivot table is a summary table. It is the most popular concept in Excel. Most data analysts use it as a handy tool to summarize theire results. `pandas` offers the `pivot_table()` function to summarize DataFrames. A DataFrame is summarized using an aggregate function, such as mean, min, max, or sum. You can download the dataset from the following

```
# Import pandas
import pandas as pd

# Load data using read_csv() purchase
= pd.read_csv("purchase.csv")

# Show initial 10 records
purchase.head(10)
```

This results in the following output:

	Weather	Food	Price	Number
0	cold	soup	3.745401	8
1	hot	soup	9.507143	8
2	cold	icecream	7.319939	8
3	hot	chocolate	5.986585	8
4	cold	icecream	1.560186	8
5	hot	icecream	1.559945	8
6	cold	soup	0.580836	8

In the preceding code block, we have read the `purchase.csv` file using the `read_csv()` method.

Now, we will summarize the dataframe using the following code:

```
# Summarise dataframe using pivot table
pd.pivot_table(purchase,values='Number', index=['Weather',],
columns=['Food'], aggfunc=np.sum)
```

This results in the following output:

Food	**chocolate**	**icecream**	**soup**
Weather			
cold	NaN	16.0	16.0
hot	8.0	8.0	8.0

In the preceding example, the `purchase` DataFrame is summarized. Here, `index` is the `Weather` column, `columns` is the `Food` column, and `values` is the aggregated sum of the `Number` column. `aggfun` is initialized with the `np.sum` parameter. It's time to learn how to deal with dates in `pandas` DataFrames.

Dealing with dates

Dealing with dates is messy and complicated. You can recall the Y2K bug, the upcoming 2038 problem, and time zones dealing with different problems. In time-series datasets, we come across dates. `pandas` offers date ranges, resamples time-series data, and performs date arithmetic operations.

Create a range of dates starting from January 1, 2020, lasting for 45 days, as follows:

```
pd.date_range('01-01-2000', periods=45, freq='D')

Output:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10', '2000-01-11', '2000-01-12',
               '2000-01-13', '2000-01-14', '2000-01-15', '2000-01-16',
               '2000-01-17', '2000-01-18', '2000-01-19', '2000-01-20',
               '2000-01-21', '2000-01-22', '2000-01-23', '2000-01-24',
               '2000-01-25', '2000-01-26', '2000-01-27', '2000-01-28',
               '2000-01-29', '2000-01-30', '2000-01-31', '2000-02-01',
               '2000-02-02', '2000-02-03', '2000-02-04', '2000-02-05',
               '2000-02-06', '2000-02-07', '2000-02-08', '2000-02-09',
               '2000-02-10', '2000-02-11', '2000-02-12', '2000-02-13',
               '2000-02-14'],
dtype='datetime64[ns]', freq='D')
```

January has less than 45 days, so the end date falls in February, as you can check for yourself.

`date_range()` freq parameters can take values such as `B` for business day frequency, `W` for weekly frequency, `H` for hourly frequency, `M` for minute frequency, `S` for second frequency, `L` for millisecond frequency, and `U` for microsecond frequency. For more details, you can refer to the official documentation at `https:// pandas. pydata. org/ pandas- docs/ stable/ user_guide/ timeseries. html` .

- **pandas date range:** The `date_range()` function generates sequences of date and time with a fixed-frequency interval:

```
# Date range function
pd.date_range('01-01-2000', periods=45, freq='D')
```

This results in the following output:

```
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10', '2000-01-11', '2000-01-12',
               '2000-01-13', '2000-01-14', '2000-01-15', '2000-01-16',
               '2000-01-17', '2000-01-18', '2000-01-19', '2000-01-20',
               '2000-01-21', '2000-01-22', '2000-01-23', '2000-01-24',
               '2000-01-25', '2000-01-26', '2000-01-27', '2000-01-28',
               '2000-01-29', '2000-01-30', '2000-01-31', '2000-02-01',
               '2000-02-02', '2000-02-03', '2000-02-04', '2000-02-05',
               '2000-02-06', '2000-02-07', '2000-02-08', '2000-02-09',
               '2000-02-10', '2000-02-11', '2000-02-12', '2000-02-13',
               '2000-02-14'],
              dtype='datetime64[ns]', freq='D')
```

- `to_datetime()`: `to_datetime()` converts a timestamp string into datetime:

```
# Convert argument to datetime
pd.to_datetime('1/1/1970') Output:

Timestamp('1970-01-01 00:00:00')
```

- We can convert a timestamp string into a datetime object in the specified format:

```
# Convert argument to datetime in specified format
pd.to_datetime(['20200101', '20200102'], format='%Y%m%d')

Output:
DatetimeIndex(['2020-01-01', '2020-01-02'], dtype='datetime64[ns]',
freq=None)
```

- **Handling an unknown format string**: Unknown input format can cause value errors. We can handle this by using an errors parameter with `coerce`. `coerce` will set invalid strings to NaT:

```
# Value Error pd.to_datetime(['20200101',
'not a date'])

Output:
ValueError: ('Unknown string format:', 'not a date')

# Handle value error pd.to_datetime(['20200101', 'not a
date'], errors='coerce')

Output:
DatetimeIndex(['2020-01-01', 'NaT'], dtype='datetime64[ns]',
freq=None)
```

In the preceding example, the second date is still not valid and cannot be converted into a datetime object. The errors parameter helped us to handle such errors by inputting the value `NaT` (not a time).

Summary

In this chapter, we have explored the NumPy and pandas libraries. Both libraries help deal with arrays and DataFrames. NumPy arrays have the capability to deal with n-dimensional arrays. We have learned about various array properties and operations. Our main focus is on data types, data type as an object, reshaping, stacking, splitting, slicing, and indexing.

We also focused on the `pandas` library for Python data analysis. We saw how `pandas` mimics the relational database table functionality. It offers functionality to query, aggregate, manipulate, and join data efficiently.

NumPy and `pandas` work well together as a tool and make it possible to perform basic data analysis. At this point, you might be tempted to think that `pandas` is all we need for data analysis. However, there is more to data analysis than meets the eye.

Having picked up the fundamentals, it's time to proceed to data analysis with the commonly used statistics functions in `Chapter 3`, *Statistics*. This includes the usage of statistical concepts.

You are encouraged to read the books mentioned in the *References* section for exploring NumPy and `pandas` in further detail and depth.