ARTIFICIAL INTELLIGENCE

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Contents

1 AI

Welcome to the AI manual, your guide to the rapidly evolving world of **Artificial Intelligence**. This manual provides an overview of AI technology, its various applications, and the ethical considerations surrounding its development and implementation. Whether you are a student, researcher, or industry professional, this manual offers a comprehensive introduction to the exciting and dynamic field of AI.

AI is a rapidly advancing field with groundbreaking applications. Python, with its libraries and frameworks, has become a popular language for developing AI solutions. Python's extensive libraries and frameworks, such as TensorFlow and PyTorch, provide efficient and user-friendly tools for developing AI applications.

2 Primer Concepts

Since the invention of computers or machines, their capability to perform various tasks has experienced exponential growth. Humans have developed the power of computer systems in terms of their diverse working domains, their increasing speed, and reducing size with respect to time.

A branch of Computer Science named Artificial Intelligence pursues creating computers or machines as intelligent as human beings.

2.1 Basic Concept of Artificial Intelligence (AI)

According to the father of Artificial Intelligence, John McCarthy, it is “The science and engineering of making intelligent machines, especially intelligent computer programs”.

Artificial Intelligence is a way of making a computer, a computer-controlled robot, or software think intelligently, in a similar manner to intelligent humans think. AI is accomplished by studying how the human brain thinks and how humans learn, decide, and work while trying to solve a problem, and then using the outcomes of this study as a basis for developing intelligent software and systems.

While exploiting the power of AI started with intention of creating similar intelligence in machines that we find and regard as high in humans.

2.2 The Necessity of Learning AI

As we know that AI pursues creating machines as intelligent as human beings. There are numerous reasons for us to study AI. The reasons are as follows -

AI can learn through data

In our daily life, we deal with a huge amount of data and the human brain cannot keep track of so much data. That is why we need to automate things. For automation, we need to study AI because it can learn from data and can do repetitive tasks with accuracy and without tiredness.

AI can teach itself

It is very necessary that a system should teach itself because the data itself keeps changing and the knowledge which is derived from such data must be updated constantly. We can use AI to fulfill this purpose because an AI-enabled system can teach itself.

AI can respond in real-time

Artificial intelligence with the help of neural networks can analyze the data more deeply. Due to this capability, AI can think and respond to situations that are based on the conditions in real time.

AI achieves accuracy

With the help of deep neural networks, AI can achieve tremendous accuracy. AI helps in the field of medicine to diagnose diseases such as cancer from the MRIs of patients.

AI can organize data to get the most out of it

The data is an intellectual property for the system which are using self-learning algorithms. We need AI to index and organize the data in a way that always gives the best results.

Understanding Intelligence

With AI, smart systems can be built. We need to understand the concept of intelligence so that our brain can construct another intelligence system like itself.

2.3 What is Intelligence?

The ability of a system to calculate, reason, perceive relationships and analogies, learn from experience, store and retrieve information from memory, solve problems, comprehend complex ideas, use the *natural language fluently, classify, generalize,* and *adapt to new situations*.

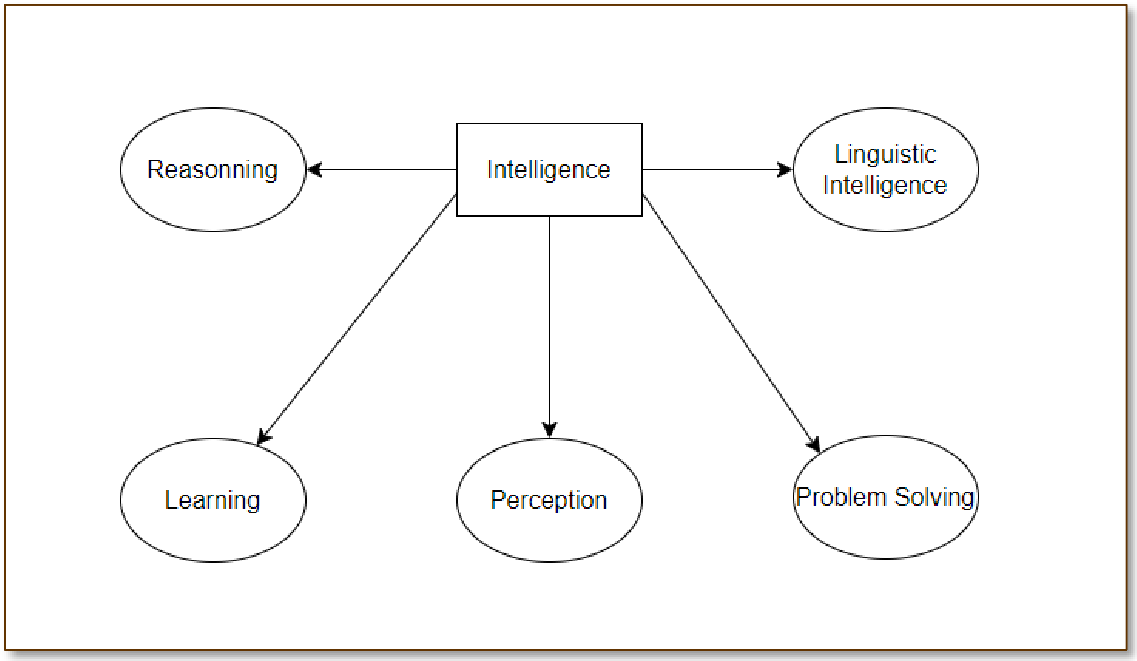
Sr.No	Intelligence & Description	Example
1	**Linguistic intelligence**. The ability to speak, recognize, and use mechanisms of phonology (speech sounds), syntax (grammar), and semantics (meaning).	**Narrators, Operators**
2	**Musical intelligence**. The ability to create, communicate with, and undestand meanings made of sound, understanding of pitchm rhythm.	**Musicians, Singers, Composers**
3	**Logical-mathemetical intelligence**. The ability to use and undestand relationships in the absence of action or objects. It is also the ability to understand complex and abstract ideas.	**Mathematicians, Scientists**
4	**Spatial intelligence**. The ability to perceive visual or spacial information, change it, and re-create visual images without reference to the objects, construct 3D images, and to move and rotate them.	**Map readers, Astronauts, Physicists**
5	**Bodily-Kinesthetic intelligence**. The abiility to use complete or part of the body to solve problems or fashion products, control over fine and coarse motor skills, and manipulate the objects.	**Players, Dancers**
6	**Intra-personal intelligence**. The ability to distinguish among one's own feelings, intentions, and motivations.	**Gautam Buddhha**
7	**Interpersonal intelligence**. The ability to recognize and make distinctions among other people's feelings, beliefs, and intentions.	**Mass Communicators, Interviewers**

You can say a machine or a system is artificially intelligent when it is equipped with a least one or all intelligence in it.

2.4 What is Intelligence Composed Of?

Intelligence is intangible. It is composed of:

- Reasoning
- Learning
- Problem-Solving
- Perception
- Linguistic Intelligence



Intelligence

Reasoning

It is the set of processes that enables us to provide the basis for judgment, making decisions, and prediction. There are broadly two types:

1. **Inductive Reasoning**

- It conducts specific observations to make broad general statements.
- Even if all of the premises are true in a statement, inductive reasoning allows for the conclusion to be false.

Example: *Nita is a teacher, Nita is studious. Therefore, All teachers are studious.*

2. **Deductive Reasoning**

- It starts with a general statement and examines the possibilities to reach a specific, logical conclusion.
- If something is true of a class of things in general, it is also true for all members of that class.

Example: *All women of age above 60 years are grandmothers. Shalini is 65 years. Therefore, Shalini is a grandmother.*

Learning - 1

The ability of learning is processed by humans, particular species of animals, and AI-enabled systems. Learning is categorized as follows:

1. **Auditory Learning**
   It is learning by listening and hearing. For example, students listen to recorded audio lectures.
2. **Episodic Learning**
   To learn by remembering sequences of events that one has witnessed or experienced. This is linear and orderly.
3. **Motor Learning**
   It is learning by the precise movement of muscles. For example, picking objects, writing, etc.
4. **Observational Learning**
   To learn by watching and imitating others. For example, the child tries to learn by mimicking her parent.
5. **Perceptual Learning**
   It is learning to recognize stimuli that one has seen before. For example, identifying and classifying objects and situations.
6. **Relational Learning**
   It involves learning to differentiate among various stimuli on the basis of relational properties, rather than absolute properties. For Example, Add 'little less' salt at the time of cooking potatoes that came up salty last time, when cooked with adding say a tablespoon of salt.

Spatial Learning

It is learning through visual stimuli such as images, colors, maps, etc. For example, A person can create a roadmap in mind before actually following the road.

Stimulus-Response Learning

It is learning to perform a particular behavior when a certain stimulus is present. For example, a dog raises its ear on hearing a doorbell.

7. **Problem-Solving**

- It is the process in which one perceives and tries to arrive at a desired solution from a present situation by taking some path, which is blocked by known or unknown hurdles.
- Problem-solving also includes **decision-making**, which is the process of selecting the best suitable alternative out of multiple alternatives to reach the desired goal.

8. **Perception**

- It is the process of acquiring, interpreting, selecting, and organizing sensory information.
- Perception presumes **to sense**. In humans, perception is aided by sensory organs. In the domain of AI, the perception mechanism puts the data acquired by the sensors together in a meaningful manner.

9. **Linguistic Intelligence**

   It is one's ability to use, comprehend, speak, and write the verbal and written language. It is important in interpersonal communication.

2.5 What's Involved in AI

Artificial intelligence is a vast area of study. This field of study helps in finding solutions to real-world problems. Let us now see the different fields of study within AI:

1. **Machine Learning**
   It is one of the most popular fields of AI. The basic concept of this field is to make machine learning from data as human beings can learn from his/her experience. It contains learning models on the basis of which the predictions can be made on unknown data.
2. **Logic**
   It is another important field of study in which mathematical logic is used to execute computer programs. It contains rules and facts to perform pattern matching, semantic analysis, etc.
3. **Searching**
   This field of study is basically used in games like chess, and tic-tac-toe. Search algorithms give the optimal solution after searching the whole search space.
4. **Artificial neural networks**
   This is a network of efficient computing systems the central theme of which is borrowed from the analogy of biological neural networks. ANN can be used in robotics, speech recognition, speech processing, etc.
5. **Genetic Algorithm**
   Genetic algorithms help in solving problems with the assistance of more than one program. The result would be based on selecting the fittest.
6. **Knowledge Representation**
   It is the field of study with the help of which we can represent the facts in a way the machine that is understandable to the machine. The more efficiently knowledge is represented, the more system would be intelligent.

2.6 Application of AI

In this section, we will see the different fields supported by AI.

1. **Gaming**

   AI plays a crucial role in strategic games such as chess, poker, tic-tac-toe, etc., where machines can think of a large number of possible positions based on heuristic knowledge.

2. **Natural Language Processing**

   It is possible to interact with the computer that understands the natural language spoken by humans.

3. **Expert Systems**

   There are some applications that integrate machines, software, and special information to impact reasoning and advising. They provide explanations and advice to the users.

4. **Vision Systems**

   These systems understand, interpret, and comprehend visual input on the computer. For **example**:

   A spying airplane takes photographs, which are used to figure out spatial information or map of the areas.

   Doctors use a clinical expert system to diagnose the patient.

   Police use computer software that can recognize the face of criminals with the stored portrait made by forensic artists.

5. **Speech Recognition**

   Some intelligent systems are capable of hearing and comprehending the language in terms of sentences and their meanings while a human talks to it. It can handle different accents, slang words, noise in the background, changes in human noise due to cold, etc.

6. **Handwriting Recognition**

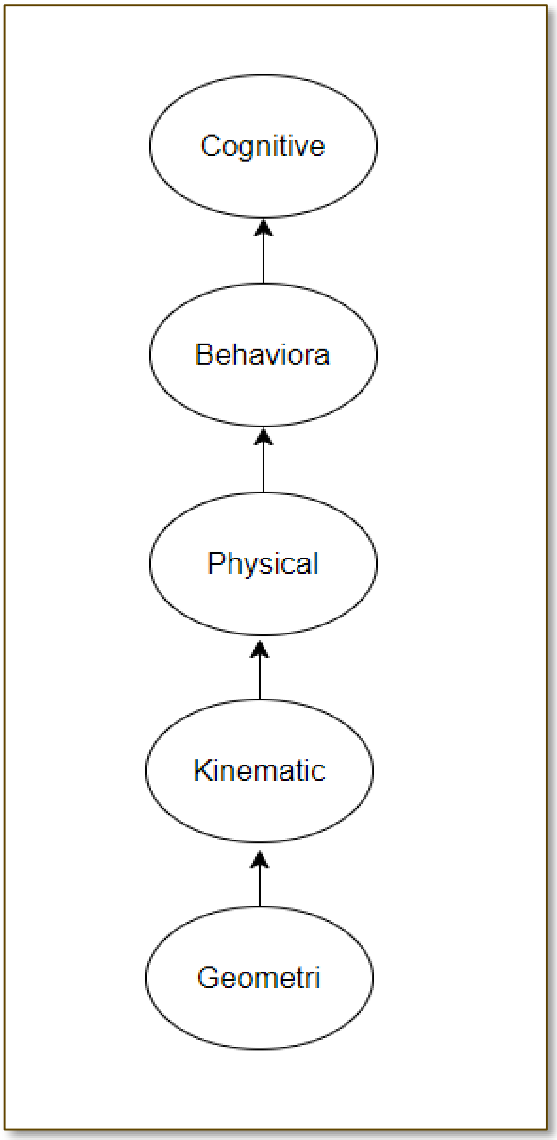
   The handwriting recognition software reads the text written on paper with a pen or on screen by a stylus. It can recognize the shapes of the letters and convert them into editable text.

7. **Intelligent Robots**

   Robots are able to perform the tasks given by a human. They have sensors to detect physical data from the real world such as light, heat, temperature, movement, sound, bumps, and pressure. They have efficient processors, multiple sensors, and huge memory, to exhibit intelligence. In addition, they are capable of learning from their mistakes and can adapt to the new environment.

2.7 Cognitive Modeling: Simulating Human Thinking Procedure

Cognitive modeling is basically the field of study within computer science that deals with the study and simulation of the thinking process of human beings. The main task of AI is to make machines think like humans. The most important feature of the human thinking process is problem-solving. That is why more or less cognitive modeling tries to understand how humans can solve problems. After that this model can be used for various AI applications such as machine learning, robotics, natural language processing, etc. Following is the diagram of the different thinking levels of the human brain:



Thinking levels

2.8 Agent & Environment

In this section, we will focus on the agent and environment and how these help in Artificial Intelligence.

Agent

An agent is anything that can perceive its environment through sensors and act upon that environment through effectors.

- A **human agent** has sensory organs such as eyes, ears, nose, tongue, and skin parallel to the sensors, and other organs such as hands, legs, and mouth, for effectors.
- A **robotic agent** replaces cameras and infrared range finders for the sensors, and various motors and actuators for effectors.
- A **software agent** has encoded bit strings as its programs and actions.

Environment

Some programs operate in an entirely **artificial environment** confined to keyboard input, database, computer file systems, and character output on a screen.

In contrast, some software agents (software robots or softbots) exist in rich, unlimited softbots domains. The simulator has a **very detailed, complex environment**. The software agent needs to choose from a long array of actions in real-time. A softbot is designed to scan the online preferences of the customer and shows interesting items to the customer who works in the **real** as well as an **artificial** environment.

3 Getting Started

In this chapter, we will learn how to get started with Python. We will also understand how Python helps with Artificial Intelligence.

3.1 Why Python for AI

Artificial intelligence is considered to be the trending technology of the future. Already there are a number of applications made on it. Due to this, many companies and researchers are taking interest in it. But the main question that arises here is in which programming language can these AI applications be developed? There are various programming languages like Lisp, Prolog, C++, Java, and Python, which can be used for developing applications of AI. Among them, Python programming language gains huge popularity and the reasons as follows:

1. **Simple syntax & less coding**

   Python involves very less coding and simple syntax than other programming languages which can be used for developing AI applications. Due to the feature, the testing can be easier and we can focus more on programming.

2. **Inbuilt libraries for AI projects**

   A major advantage of using Python for AI is that it comes with inbuilt libraries. Python has libraries for almost all kinds of AI projects. For example, **NumPy**, **SciPy**, **matplotlib**, **nltk**, and **SimpleAI** are some of the important inbuilt libraries of Python.

   Open Source

   Python is an open-source programming language. This makes it widely popular in the community.

   Can be used for a broad range of programming

   Python can be used for a broad range of programming tasks from small shell scripts to enterprise web applications. This is another reason Python is suitable for AI projects.

3.2 Features of Python

Python is a high-level, interpreted, interactive, and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently where as other languages use punctuation, and it has fewer syntactical constructions than other languages. Python's features include the following:

- **Easy-to-learn** - Python was few keywords, a simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.
- **Easy-to-read** - Python code is more clearly defined and visible to the eyes.
- **Easy-to-maintain** - Python's source code is fairly easy-to-maintain.
- **A broad standard library** - Python's bulk of the library is very portable and cross-platform compatible on *UNIX*, *Windows*, and *Macintosh*.
- **Interactive Mode** - Python has support for an interactive mode that allows interactive testing and debugging of snippets of code.
- **Portable** - Python can run on a wide variety of hardware platforms and has the same interface on all platforms.
- **Extendable** - We can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- **Databases** - Python provides interfaces to all major commercial databases.
- **GUI Programming** - Python supports GUI applications that can be created and ported to many system calls, libraries, and windows systems, such as *Windows MFC*, *Macintosh*, and the *X Windows system of Unix*.
- **Scalable** - Python provides a better structure and support for large programs than shell scripting.

Important features of Python

Let us now consider the following important features of Python:

- It supports functional and structured programming methods as well as *OOP*.
- It can be used as a scripting language or can be compiled to byte code for building large applications.
- It provides very high-level dynamic data types and supports dynamic type checking.
- It supports automatic garbage collection.
- It can be easily integrated with *C*, *C++*, *COM*, *ActiveX*, *CORBA*, and *Java*.

3.3 Installing Python

Python distribution is available for a large number of platforms. You need to download only the binary code applicable to your platform and install Python.

If the binary code for your platform is not available, you need a C compiler to compile the source code manually. Compiling the source code offers more flexibility in terms of the choice of features that you require in your installation. Here is a quick overview of the features that you require in your installation.

Here is a quick overview of installing Python on various platforms:

1. **Unix and Linux installation**

- Follow these steps to install Python on Unix/Linux machine.
    - Open a Web browser and go to `https://www.python.org/download`
    - Follow the link to download the zipped source code available for Unix/Linux.
    - Download and extract files.
    - Editing the *`Modules/Setup`* file if you want to customize some options.
    - run ./configure script
    - make
    - make install
- This installs Python at the standard location *`/usr/local/bin`* and its libraries at *`/usr/local/lib/pythonXX`* where *XX* is the version of Python.

2. **Windows Installation**

- Follow these steps to install Python on a *Windows* machine.
- Follow the link for the *Windows* installer *`python-XYZ.msi`* file where *XYZ* is the version you need to install.
- To use this installer *`python-XYZ.msi`*, the *Windows* system must support *Microsoft Installer 2.0*. Save the installer file to your local machine and then run it to find out if your machine supports MSI.
- Run the downloaded file. This brings up the Python install wizard, which is really easy to use. Just accept the default settings and wait until the installation is finished.

3. **Macintosh Installation**

   If you are on *MAC OS X*, it is recommended that you use *Homebrew* to install Python 3. It is a great package installer for *Mac OS X* and it is really easy to use. If you don't have *Homebrew*, you can install it using the following command:

   ```
   $ ruby -e "$(curl -fsSL
   https://raw.githubusercontent.com/Homebrew/install/master/install)"
   ```

We can update the package manager with the command below:

```
$ brew update
```

Now run the following command to install Python 3 on your system:

```
$ brew install python3
```

3.4 Setting up PATH

Programs and other executable files can be in many directories, so operating systems provide a search path that lists the directories that the OS searches for executables.

The path is stored in an environment variable, which is a named string maintained by the operating system. This variable contains information available to the command shell and other programs.

The path variable is named *PATH in Unix* or *Path in Windows* (Unix is case-sensitive, Windows is not).

In *Mac OS*, the installer handles the path details. To invoke the Python interpreter from any particular directory, you must add the Python directory to your path.

Setting Path at Unix/Linux

To add the Python directory to the past for a particular session in *Unix*:

- In the *csh shell*

  ```
  setenv PATH "$PATH:/usr/local/bin/python"
  ```

- In the *bash shell (Linux)*

  ```
  export ATH = "$PATH:/usr/local/bin/python"
  ```

- In the sh or ksh shell

  ```
  PATH = "$PATH:/usr/local/bin/python"
  ```

Note: */usr/local/bin/python* is the path of the Python directory.

Setting a Path at Windows

To add the Python directory to the path for a particular session in *Windows*:

- At the command prompt

  ```
  path %path%;C:\Python
  ```

Note: *C:\* is the path of the Python directory.

3.5 Running Python

Let us now see the different ways to run Python. The ways are described below:

Interactive Interpreter

We can start Python from *Unix*, *DOS*, or any other system that provides you with a command-line interpreter or shell window.

- Enter **python** at the command line.
- Start coding right away in the interactive interpreter.

```
$python # Unix/Linux
```

Or

```
python% # Unix/Linux
```

Or

```
C:> python # Windows/DOS
```

Here is the list of all the available command line options:

S.No.	Option & Description
1	**-d** It provides debug output.
2	**-o** It generates optimized bytecode (resulting in .pyo files)
3	**-s** Do not run the import site to look for Python paths on startup.
4	**-v** Verbose output (detailed trace on import statements).
5	**-x** Disables class-based built-in exceptions (just use strings), obsolete starting with version 1.6
6	**-c cmd** Runs Python script sent in as a cmd string.
7	**File** Run Python script from the given file.

3.6 Script from the Command-line

A Python script can be executed at the command line by invoking the interpreter on your application, as in the following:

```
$python script.py # Unix/Linux
```

Or

```
python% script.py # Unix/Linux
```

Or

```
C:> python script.py # Windows/DOS
```

Note: Be sure the file permission mode allows execution.

3.7 Integrated Development Environment

You can run Python from a *Graphical User Interface (GUI)* environment as well if you have a GUI application on your system that supports Python.

- **Unix** - IDLE is the very first *Unix IDE* for Python.
- **Windows** - PythonWin is the first Windows interface for Python and is an *IDE* with a GUI.
- **Macintosh** - The Macintosh version of Python along with the *IDLE IDE* is available from the main website, downloadable as either MacBinary or BinHex files.

If you are not able to set up the environment properly, then you can take help from your system admin. Make sure the Python environment is properly set up and working perfectly fine.

We can also use another Python platform called Anaconda. It includes hundreds of popular data science packages and the conda package and virtual environment manager for *Windows, Linux*, and *MacOS*. You can download it as per your operating system from the link `https://www.anaconda.com/download/`.

For this tutorial, we are using Python 3.6.3 version on *MS Windows*.

4 Machine Learning

Learning means the acquisition of knowledge or skills through study or experience. Based on this, we can define *machine learning (ML)* as follows:

It may be defined as the field of computer science, more specifically an application of artificial intelligence, which provides computer systems the ability to learn with data and improve from experience without being explicitly programmed.

Basically, the main focus of machine learning is to allow computers to learn automatically without human intervention. Now the question arises that how such learning can be started and done. It can be started with the observation of data. The data can be some examples, instruction, or direct experiences too. Then on the basis of this input, the machine makes better decisions by looking for some patterns in the data.

4.1 Types of Machine Learning (ML)

Machine Learning Algorithms helps computer system learn without being explicitly programmed. These algorithms are categorized into supervised or unsupervised. Let us now see a few algorithms:

Supervised machine learning algorithms

This is the most commonly used machine learning algorithm. It is called supervised because the process of algorithm learning from the training dataset can be thought of as a teacher supervising the learning process. In this kind of ML algorithm, the possible outcomes are already known and training data is also labeled with correct answers. It can be understood as follows:

Suppose we have an input variable **x** and an output variable **y** and we applied an algorithm to learn the mapping function from the input to output such as

Y = f(x)

Now, the main goal is to approximate the mapping function so well that when we have new input data **(x)**, we can predict the output variable **(Y)** for that data.

Mainly supervised learning problems can be divided into the following two kinds of problems:

- **Classification** - A problem is called a classification problem when we have the categorized output such as *"black", "teaching", "non-teaching", etc*.
- **Regression** - A problem is called regression problem when we have the real value output such as *"distance", "kilogram", etc.*

Decision tree, random forest, knn, and logistic regression are examples of supervised machine learning algorithms.

Unsupervised machine learning algorithms

As the name suggests, these kinds of machine learning algorithms do not have any supervisor to provide any sort of guidance. That is why unsupervised machine learning algorithms are closely aligned with what some call true artificial intelligence. It can be understood as follows:

Suppose we have input variable **x**, then there will be no corresponding output variables as there are in supervised learning algorithms.

In simple words, we can say that in unsupervised learning there will be no correct answer and no teacher for guidance. Algorithms help to discover interesting patterns in data.

Unsupervised learning problems can be divided into the following two kinds of problems:

- **Clustering** - In clustering problems, we need to discover the inherent groupings in the data. For example, grouping customers by their purchasing behavior.
- **Association** - A problem is called an association problem because such kinds of problems require discovering the rules that describe large portions of our data. For example, finding the customers who buy both **x** and **y**.

K-means for clustering, and the Apriori algorithm, for the association, are examples of unsupervised machine learning algorithms.

Reinforcement machine learning algorithms

These kinds of machine learning algorithms are used very less. These algorithms train the system to make specific decisions. Basically, the machine is exposed to an environment where it trains itself continually using the trial and error method. These algorithms learn from past experience and try to capture the best possible knowledge to make accurate decisions. *Markov Decision Process* is an example of reinforcement machine learning algorithms.

4.2 Most Common Machine Learning Algorithms

In this section, we will learn about the most common machine learning algorithms. The algorithms are described below:

Linear Regression

It is one of the most well-known algorithms in statistics and machine learning.

Basic concept: Mainly linear regression is a linear model that assumes a linear relationship between the input variables say **x** and the single output variable say **y**. In other words, we can say that y can be calculated from a linear combination of the input variables **x**. The relationship between variables can be established by fitting the best line.

- **Simple linear regression:** A linear regression algorithm is called simple linear regression if it is having only one independent variable.
- **Multiple linear regression:** A linear regression algorithm is called multiple linear regression if it is having more than one independent variable.

Linear regression is mainly used to estimate the real values based on a continuous variable(s). For example, the total sale of a shop in a day, based on real values, can be estimated by linear regression.

Logic Regression

It is a classification algorithm also known as **logit** regression.

Mainly logistic regression is a classification algorithm that is used to estimate discrete values like **0** or **1**, true or false, and yes or no based on a given set of independent variables. Basically, it predicts the probability hence its output lies between **0** and **1**.

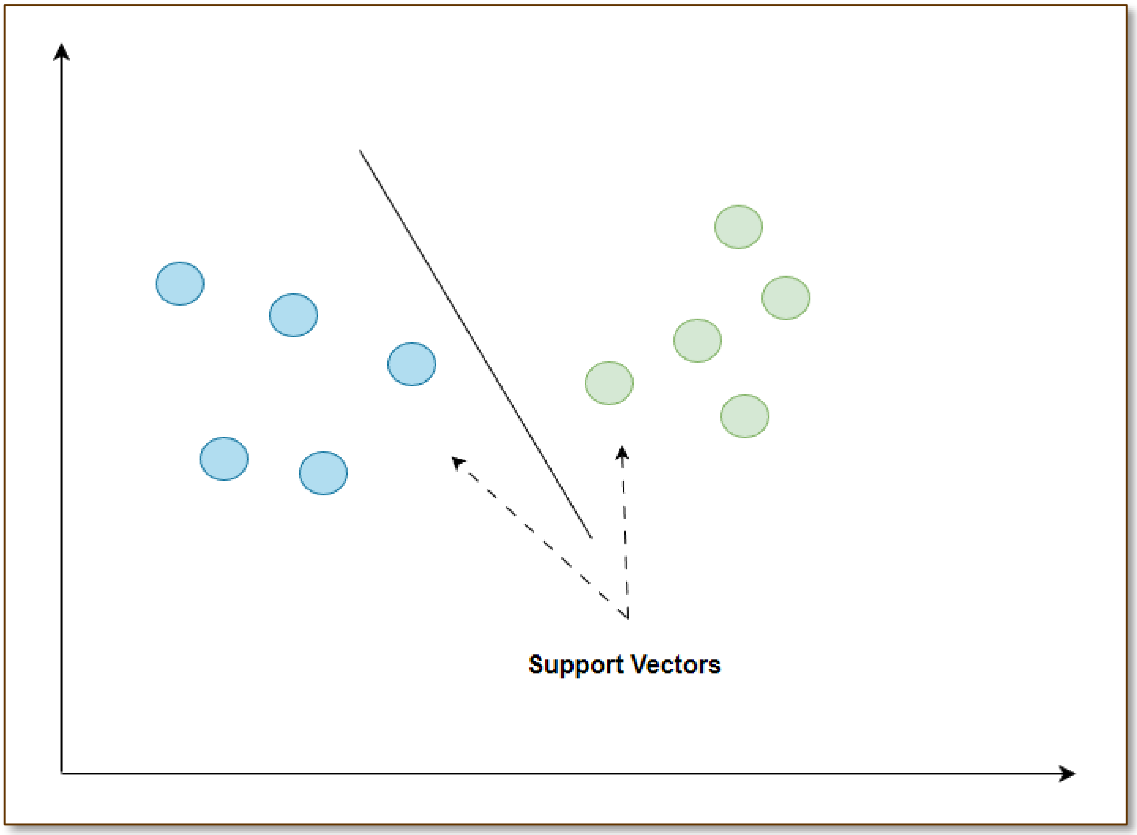
Decision Tree

Decision tree is a supervised learning algorithm that is mostly used for classification problems.

Basically, it is a classifier expressed as a recursive partition based on the independent variables. The decision tree has nodes that form the rooted tree. A rooted tree is a directed tree with a node called a *"root"*. The root does not have any incoming edges and all the other nodes have one incoming edge. These nodes are called leaves or decision nodes. For example, consider the following decision tree to see whether a person is fit or not.

Support Vector Machine (SVM)

It is used for both classification and regression problems. But mainly it is used for classification problems. The main concept of SVM is to plot each data item as a point in *n-dimensional space* with the value of each feature being the value of a particular coordinate. Here n would be the features we would have. Following is a simple graphical representation to understand the concept of SVM.



Vectors

In the above diagram, we have two features hence we first need to plot these two variables in two-dimensional space where each point has two coordinates, called support vectors. The line splits the data into two different classified groups. This line would be the classifier.

Naive Bayes

Is also a classification technique. The logic behind this classification technique is to use the Bayes theorem for building classifiers. The assumption is that the predictors are independent. In simple words, it assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. Below is the equation for Bayes theorem:

$$P\left (\frac{A}{B}\right) = \frac{P\left (\frac{B}{A}\right)P\left (A \right)}{P\left (B \right)}$$

The Naive Bayes model is easy to build and particularly useful for large data sets.

K-Nearest Neighbors (KNN)

It is used for both classification and regression of the problems. It is widely used to solve classification problems. The main concept of the algorithm is that it is used to store all the available cases and classifies new cases by the majority votes of its *k neighbors*. The case is then assigned to the class which is the most common amongst its *K-nearest neighbors*, measured by a distance function. The distance function can be *Euclidean, Minkowski,* and *Hamming* distance. Consider the following to use *KNN*:

- Computationally *KNN* are expensive than other algorithms used for classification problems.
- The normalization of variables is needed otherwise higher range variables can bias it.
- In *KNN*, we need to work on pre-processing stages like noise removal.

K-Means Clustering

As the name suggests, it is used to solve clustering problems. It is basically a type of unsupervised learning. The main logic of the *K-Means* clustering algorithm is to classify the data set through a number of clusters. Follow these steps to form clusters by *K-means:*

- K-means picks k number of points for each cluster known as centroids.
- Now each data point forms a cluster with the closest centroids, i.e., k clusters.
- Now, it will find the centroids of each cluster based on the existing cluster members.
- We need to repeat these steps until convergence occurs.

Random Forest

It is a supervised classification algorithm. The advantage of the random forest algorithm is that it can be used for both classification and regression kind of problems. Basically, it is the collection of decision trees (i.e., forest) or you can say ensemble of the decision trees. The basic concept of random forest is that each tree gives a classification and the forest chooses the best classifications from them. The followings are the advantages of the Random Forest algorithm:

- Random forest classifier can be used for both classification and regression tasks.
- They can handle the missing values.
- It won't over fit the model even if we have more trees in the forest.

5 Data Preparation

We have already studied supervised as well as unsupervised machine learning algorithms. These algorithms require formatted data to start the training process. We must prepare or format data in a certain way so that it can be supplied as input to ML algorithms.

This chapter focuses on data preparation for machine learning algorithms.

5.1 Preprocessing the Data

In our daily life, we deal with lots of data but this data is in raw form. To provide the data as the input of machine learning algorithms, we need to convert it into meaningful data. That is where data preprocessing comes into the picture. In other simple words, we can say that before providing the data to the machine learning algorithms w need to preprocess the data.

Data preprocessing steps

Follow these steps to preprocess the data in Python:

Step 1 - Importing the useful packages - If we are using Python then this would be the first step for converting the data into a certain format, i.e., preprocessing it can be done as follows:

```
import numpy as np
import sklearn.preprocessing
```

We have used the following two packages:

- **NumPy** - Basically *NumPy* is a general-purpose array-processing package designed to efficiently manipulate large multi-dimensional arrays of arbitrary records without sacrificing too much speed for small multi-dimensional arrays.
- **Sklearn. preprocessing** - This package provides many common utility functions and transformer classes to change raw feature vectors into a representation that is more suitable for machine learning algorithms.

Step 2 - Defining sample data - After importing the packages, we need to define some sample data so that we can apply preprocess techniques to that data. We will now define the following sample data:

```
Input_data = np.array([2.1,  -1.9,  5.5],
                      [-1.5,  2.4   3.5],
                      [0.5,  -7.9,  5.6],
                      [5.9,   2.3, -5.8],)
```

Step3 - Applying preprocessing technique - In this step, we need to apply any of the preprocessing techniques.

The following section describes the data preprocessing techniques.

5.2 Techniques for Data Preprocessing

The techniques for data preprocessing are described below:

Binarization

This is the preprocessing technique that is used when we need to convert our numerical values into Boolean values. We can use an inbuilt method to binarize the input data say by using **0.5** as the threshold value in the following way:

```
  data_binarized = preprocessing.Binarizer(threshold = 0.5).transform(imput)
print("\nBinarized data:\n", data_binarized)
```

Now after running the above code we will get the following output, all the values above **0.5***(threshold values)* would be converter to **1** and all the values below **0.5** would be converted to **0**.

Binarized data

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

Mean Removal

It is another very common preprocessing technique that is used in machine learning. Basically, it is used to eliminate the mean from the feature vector so that every feature is centered on zero. We can also remove the bias from the feature in the feature vector. For applying the mean removal preprocessing technique on the sample data, we can write the Python code shown below. The code will display the *Mean and Standard deviation* of the input data:

```
      print("Mean = ", input_data.mean(axis = 0))
      print("Std deviation = ", input_)data.std(axis = 0)
```

We will get the following output after running the above line of code:

```
               Mean = [1.75       -1.275       2.2]
      Std deviation = [2.71431391 4.20022321 4.69414529]
```

Now, the code below will remove the Mean and Standard deviation of the input data:

```
      data_scaled = preprocessing.scale(input_data)
      print("Mean =", data_scaled.mean(axis=0))
      print("Std deviation =", data_scaled.std(axis = 0))
```

We will get the following output after running the above lines of code:

```
               Mean = [1.110022302e-16 0.0000000e+00 0.0000000e+00]
      Std deviation = [1.              1.             1.]
```

Scaling

It is another data preprocessing technique that is used to scale the feature vectors. *Scaling of feature vectors* is needed because the values of every feature can vary between many random values. In other words, we can say that scaling is important because we do not want any feature to be synthetically large or small. With the help of the following Python code, we can do the scaling of our input data, i.e. feature vector:

Min-max scaling

```
data_scaler_minmax = preprocessing.MinMaxScaler(feature_range=(0,1))
data_scaled_minmax = data_scaler_minmax.fit_transform(input_data)
print ("\nMin max scaled data:\n", data_scaled_minmax)
```

We will get the following output after running the above lines of code:

Min-max scaled data

```
[ [ 0.48648649  0.58252427  0.99122807]
  [ 0.          1.          0.81578947]
  [ 0.27027027  0.          1.        ]
  [ 1.          0.99029126  0.        ] ]
```

Normalization

It is another data preprocessing technique that is used to modify the feature vectors. Such kind of modification is necessary to measure the feature vectors on a common scale. The followings are two types of normalization that can be used in machine learning:

L1 Normalization

Is also referred to as **Least Absolute Deviations**. This kind of normalization modifies the values so that the sum of the absolute values is always up to **1** in each row it can be implemented on the input data with the help of the following Python code:

```
# Normalize data
data_normalized_l1 = preprocessing.normalize(input_data, norm ='l1')
print("\nL1 normalized data:\n", data_normalized_l1)
```

The above line of code generates the following output & minus;

```
L1 normalized data:
[[  0.22105236   -0.2           0.57894737]
 [ -0.2027027     0.342432432   0.47297297]
 [  0.03571429   -0.54628571    0.4        ]
 [  0.42142857    0.16428571   -0.41428571]]
```

L2 Normalization

It is also referred to as **least squares**. This kind of normalization modifies the values so that the sum of the squares is always up to **1** in each row. It can be implemented on the input data with the help of the following Python code:

```
# Normalize data
data_normalized_l2 = preprocessing.normalize(input_data, norm = 'l2')
print("\nL2 normalized data:\n", data_normalized_l2)
```

The above line of code will generate the following output:

```
L2 normalized data:
[[ 0.33946114   -0.30713151     0.88906489]
 [-0.33325106    0.53320169     0.7775858 ]
 [ 0.05156558   -0.81473612     0.57753446]
 [ 0.68706914    0.26784051    -0.6754239 ]]
```

Labeling the data

We already know that data in a certain format is necessary for machine learning algorithms. Another important requirement is that the data must be labeled properly before sending it as the input of machine learning algorithms. For example, if we talk about classification, there are a lot of labels on the data. Those labels are in the form of words, numbers, etc. Functions related to machine learning in **sklearn** expect that the data much have number labels. Hence, if the data is in another form then it must be converted to numbers. The process of transforming the word labels into numerical form is called label encoding.

Label encoding steps

Follow these steps for encoding the data labels in Python.

Step 1 - Importing the useful packages - If we are using Python then this would be the first step for converting the data into a certain format, i.e., preprocessing. It can be done as follows:

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

Step 2- Defining sample labels - After importing the packages, we need to define some sample labels so that we can create and train the label encoder. We will now define the following sample labels:

```
# Sample_input labels
input_labels = ['red', 'black', 'green', 'black', 'yellow', 'white']
```

Step 3 - Creating & training label encoder object - In this step, we need to create the label encoder and train it. The following Python code will help in doing this:

```
# Creating the label encoder
encoder = preprocessing.labelEncoder()
encoder.fit(input_labels)
```

Following would be the output after running the above Python code:

```
LabelEncoder()
```

Step 4 - Checking the performance by encoding random order list - This step can be used to check the performance by encoding the randomly ordered list. Following Python code can be written to do the same:

```
# encoding a set of labels
text_labels = ['green', 'red', 'black']
encoded_values = encoder.transform(test_labels)
print("\nLabels = ", test_labels)
```

The labels would get printed as follows:

```
Labels = ['green', 'red', 'black']
```

Now, can we get the list of encoded values i.e. word labels converted to numbers as follows:

```
print("Encoded values =", list(envoded_values))
```

The encoded values would get printed as follows

```
Encoded values = [1, 2, 0]
```

Step 5 - Checking the performance by decoding a random set of numbers - This step can be used to check the performance by decoding the random set of numbers. Following Python code can be written to do the same:

```
# decoding a set of values
endoded_values = [3, 0, 4, 1]
decoded_list = encoder.inverse_transform(encoded_values)
print("\nEncoded values =", encoded values)
```

Now, encoded values would get printed as follows:

```
Encoded values = [3, 0, 4, 1]
print("\nDecoded levels =", list(decoded_list))
```

Now, decoded values would get printed as follows:

```
Decoded labels = ['white', 'black', 'yellow', 'green']
```

Laveled v/s Unlabeled Data

Unlabeled data mainly consists of the sample of a natural or human-created object that can easily be obtained from the world. They include *audio, video, photos, news articles, etc*.

On the other hand, labeled data takes a set of unlabeled data and augments each piece of that unlabeled data with some tag or label, or class that is meaningful. For example, if we have a photo then the label can be put based on the content of the photo, i.e., it is a photo of a boy or a girl, or animal or anything else Labeling the data needs human expertise or judgment about a given piece of unlabeled data.

There are many scenarios where unlabeled data is plentiful and easily obtained but labeled data often requires a human/expert to annotate. Semi-supervised learning attempts to combine labeled and unlabeled data to build better models.

5.3 Classification

In this chapter, we will focus on implementing supervised learning - classification.

The classification technique or model attempts to get some conclusion from observed values. In the classification problem, we have the categorized output such as *"Black"* or *"white"* or *"Teaching" and "Non-Teaching"*. While building the classification model, we need to have a training dataset that contains data points and the corresponding labels. For example, if we want to check whether the image is of a car or not. To checking this, we will build a training dataset having the two classes related to *"car"* and *"no car"*. Then we need to train the model by using training samples. The classification models are mainly used in face recognition, spam identification, etc.

Steps for Building a Classifier in Python

For building a classifier in Python, we are going to use Python 3 and Scikit-learn which is a tool for machine learning. Follow these steps to build a classifier in Python:

Step 1 - Import Scikit-learn - This would be the very first step for building a classifier in Python. In this step, we will install a Python package called Scikit-learn which is one of the best machine-learning modules in Python. The following command will help us import the package:

```
Import Sklearn
```

Step 2 - Import Scikit-learn's dataset - In this step, we can begin working with the dataset for our machine learning model. Here, we are going to use **the** Breast Cancer Wisconsin Diagnostic Database. The dataset includes various information about breast cancer tumors, as well as classification labels of **malignat** or **benign**. The dataset has *569* instances, or data, on *569* tumors and includes information on **30** attributes, or features, such as the radius of the tumor, texture, smoothness, and area. With the help of the following command, we can import the Scikit-learn's breast cancer dataset:

```
from sklearn.datasets import load_breast_cancer
```

Now, the following command will load the dataset.

```
data = load_breast_cancer()
```

Following is a list of important dictionary keys:

- Classification label names(*target_names*)
- The actual labels(*target*)
- The attribute/feature names(*feature_names*)
- The attribute(*data*)

Now, with the help of the following command, we can create new variables for each important set of information and assign the data in other words, we can organize the data with the following command:

```
label_names = data['target_names']
labels = data['target']
feature_names = data['feature_names']
features = data ['data']
```

Now, to make it clearer we can print the class labels, the first data instance's label, our feature names and the feature's value with the help of the following commands:

```
print(label_names)
```

The above command will print the class names which are malignant and benign respectively. It is shown as the output below:

```
['malignant' 'benign']
```

Now, the command below will show that they are mapped to binary values **0** and **1**. Here **0** represents malignant cancer and 1 represents benign cancer. You will receive the following output:

```
print(labels[0])
0
```

The two commands given below will produce the feature names and feature values.

```
print(feature_names[0])
mean radius
print (features[0])
[ 1.79900000e+01 1.03800000e+01 1.22800000e+02 1.00100000e+03
  1.18400000e-01 2.77600000e-01 3.00100000e-01 1.47100000e-01
  2.41900000e-01 7.87100000e-02 1.09500000e+00 9.05300000e-02
  8.58900000e+00 1.53400000e+02 6.39900000e-03 4.90400000e-02
  5.37300000e-02 1.58700000e-02 3.00300000e-02 6.19300000e+03
  2.53800000e+01 1.73300000e+01 1.84600000e+02 2.01900000e+03
  1.22000000e-01 6.65600000e-01 7.11900000e-01 2.65400000e-01
  4.60100000e-01 1.18900000e-01]
```

From the above output, we can see that the first data instance is a malignant tumor the radius of which is `1.7990000e+01`.

Step 3 - Organizing data into sets - In this step, we will divide our data into two parts namely a training set and a test set. Splitting the data into these sets is very important because we have to test our model on unseen data. To split the data into sets, sklearn has a function called the **train_test_split()** function. With the help of the following commands, we can split the data into these sets:

```
from sklearn.model_selection import train_test_split
```

The above command will import the **train_test_split** function from sklearn and the command below will split the data into training and test data. In the example given below, we are using **40 %** of the data for testing and the remaining data would be used for training the model.

```
train, test, train_labels, test_labels = train_test_split(features)
```

Step 4 - Building the model - In this step, we will build our model. We are going to use the Naive Bayes algorithm for building the model. The following commands can be used to build the model:

```
from sklearn.naive_bayes import GaussianNB
```

The above command will import the *GaussianNB* module. Now, the following command will help you initialize the model.

```
gnb = GaussianNB()
```

We will train the model by filtering it to the data using **gnb.fit()**

```
model = gnb.fit(train, train_labels)
```

Step 5 - Evaluating the model and its accuracy - In this steps, we are going to evaluate the model by making a prediction on our test data. Then we will find out its accuracy also. For making predictions, we will use the **predict()** function. The following command will help you do this:

```
preds = gnb.predict(test)
print(preds)
[1 0 0 1 1 0 0 0 1 1 1 0 1 0 1 0 1 1 1 0 1 1 0 1 1 1 1 1 1
 0 1 1 1 1 1 1 1 0 1 0 1 1 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 0
 0 1 1 0 0 1 1 1 0 0 1 1 0 0 1 0 1 1 1 1 1 1 0 1 1 0 0 0 0
 0 1 1 1 1 1 1 1 1 0 0 1 0 0 1 0 0 1 1 1 0 1 1 0 1 1 0 0 0
 1 1 1 0 0 1 1 0 1 0 0 1 1 0 0 0 1 1 1 0 1 1 0 0 1 0 1 1 0
 1 0 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0
 1 1 0 1 1 1 1 1 1 0 0 0 1 1 0 1 0 1 1 1 1 0 1 1 0 1 1 1 0
 1 0 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 0 0 1 1 0 1]
```

The above series of **0s** and **1s** are the predicted values for the tumor classes - malignant and benign.

Now, by comparing the two arrays namely **test_labels** and **preds**, we can find out the accuracy of our model. We are going to use the **accuracy_score()** function to determine the accuracy. Consider the following command for this:

```
from sklearn.metrics import accuracy_score
print(accuracy_score(test_labels.preds))
0.951754385965
```

The result shows that the NaiveBayes classifier is **95.17 %** accurate.

Building Classifier in Python

In this section, we will learn how to build a classifier in Python.

Naive Bayes Classifier

Naive Bayes is a classification technique used to build a classifier using the Bayes theorem. The assumption is that the predictors are independent. In simple words, it assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. For building the Naive Bayes classifier we need to use the python library called scikit learn. There are three types of Naive Bayes models named **Gaussian, Multinomial, and BBernoulli** under the scikit learn package.

To build a Naive Bayes machine learning classifier model, we need the following & minus.

Dataset

We are going to use the dataset named Breast Cance Wisconsin Diagnostic Database. The dataset includes various information about breast cancer tumors, as well as a classification label of **malignant** or **benign**. The dataset has 569 instances, or data, on 569 tumors and includes information on 30 attributes, or features, such as the radius of the tumor, texture, smoothness, and area. We can import this dataset from the sklearn package.

Naive Bayes Model

For building the Naive Bayes classifier, we need the Naive Bayes model. As told earlier, there are three types of Naive Bayes models named **Gaussian, Multinomial,** and **Bernoulli** under the scikit learn package. Here, in the following example, we are going to use the Gaussian Naive Bayes model.

By using the above, we are going to build a Naive Bayes machine learning model to use the tumor information to predict whether or not a tumor is malignant or benign.

To begin with, we need to install the sklearn module. It can be done with the help of the following command:

```
Import Sklearn
```

Now, we need to import the dataset named Breast Cancer Wisconsin Diagnostic Database.

```
from sklearn.datasets import load_breast_cancer
```

Now, the following command will load the dataset.

```
data = load_breast_cancer()
```

The data can be organized as follows:

```
label_names = data ['target_names']
labels = data['target']
feature_names = data['faeture_names']
features = data['data']
```

Now, to make it clear we can print the class labels, the first data instance label, our feature names and the value of the feature with the help of the following command:

```
print(label_names)
```

The above command will print the class names which are malignant and benign respectively. It is shown as the output below:

```
['malignant' 'benign']
```

Now, the command given below will show that they are mapped to binary values **0** and **1**. Here **0** represents malignant cancer and 1 represents benign cancer. It is shown as the output below:

```
print(labels[0])
0
```

The following two commands will produce the feature names and feature values:

```
print(feature_names[0])
mean radius
print(features[0])
[ 1.79900000e+01 1.03800000e+01 1.22800000e+02 1.00100000e+03
  1.18400000e-01 2.77600000e-01 3.00100000e-01 1.47100000e-01
  2.41900000e-01 7.87100000e-02 1.09500000e+00 9.05300000e-02
  8.58900000e+00 1.53400000e+02 6.39900000e-03 4.90400000e-02
  5.37300000e-02 1.58700000e-02 3.00300000e-02 6.19300000e+03
  2.53800000e+01 1.73300000e+01 1.84600000e+02 2.01900000e+03
  1.22000000e-01 6.65600000e-01 7.11900000e-01 2.65400000e-01
  4.60100000e-01 1.18900000e-01
]
```

From the above output, we can see that the first data instance is a malignant tumor the main radius of which is `1.7990000e+01`.

For testing our model on unseen data, we need to split our data into training and testing data. It can be done with the help of the following code:

```
from sklearn.model_selection import train_test_split
```

The above command will import the **train_test_split** function from sklearn and the command below will split the data into training and test data. In the below example, we are using **40 %** of the data for testing and the remaining data would be used for training the model.

```
train, test, train_labels, test_labels =
train_test_split (feature, labels, test_size = 0.40, random_state = 42)
```

Now, we are building the model with the following command:

```
from sklearn.naive_bayes import GaussianNB
```

The above command will import the *GaussianNB* module. Now, with the command given below, we need to initialize the model.

```
gnb = GaussianNB()
```

We will train the model by fitting it to the data by using **gnb.fit()**

```
model = gnb.fit(train, train_labels)
```

Now, evaluate the model by making prediction on the test data and it can be done as follows:

```
preds = gnb.predict(test)
print(preds)
[1 0 0 1 1 0 0 0 1 1 1 0 1 0 1 0 1 1 1 0 1 1 0 1 1 1 1 1 1
 0 1 1 1 1 1 1 1 0 1 0 1 1 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 0
 0 1 1 0 0 1 1 1 0 0 1 1 0 0 1 0 1 1 1 1 1 1 0 1 1 0 0 0 0
 0 1 1 1 1 1 1 1 1 0 0 1 0 0 1 0 0 1 1 1 0 1 1 0 1 1 0 0 0
 1 1 1 0 0 1 1 0 1 0 0 1 1 0 0 0 1 1 1 0 1 1 0 0 1 0 1 1 0
 1 0 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0
 1 1 0 1 1 1 1 1 1 0 0 0 1 1 0 1 0 1 1 1 1 0 1 1 0 1 1 1 0
 1 0 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 0 0 1 1 0 1]
```

The above series of **0s** and **1s** are the predicted values for the tumor classes i.e. malignant and benign.

Now, by comparing the two arrays namely **test_labels** and **preds**, we can find out the accuracy of our model. We are going to use the **accuracy_score()** function to determine the accuracy. Consider the following command:

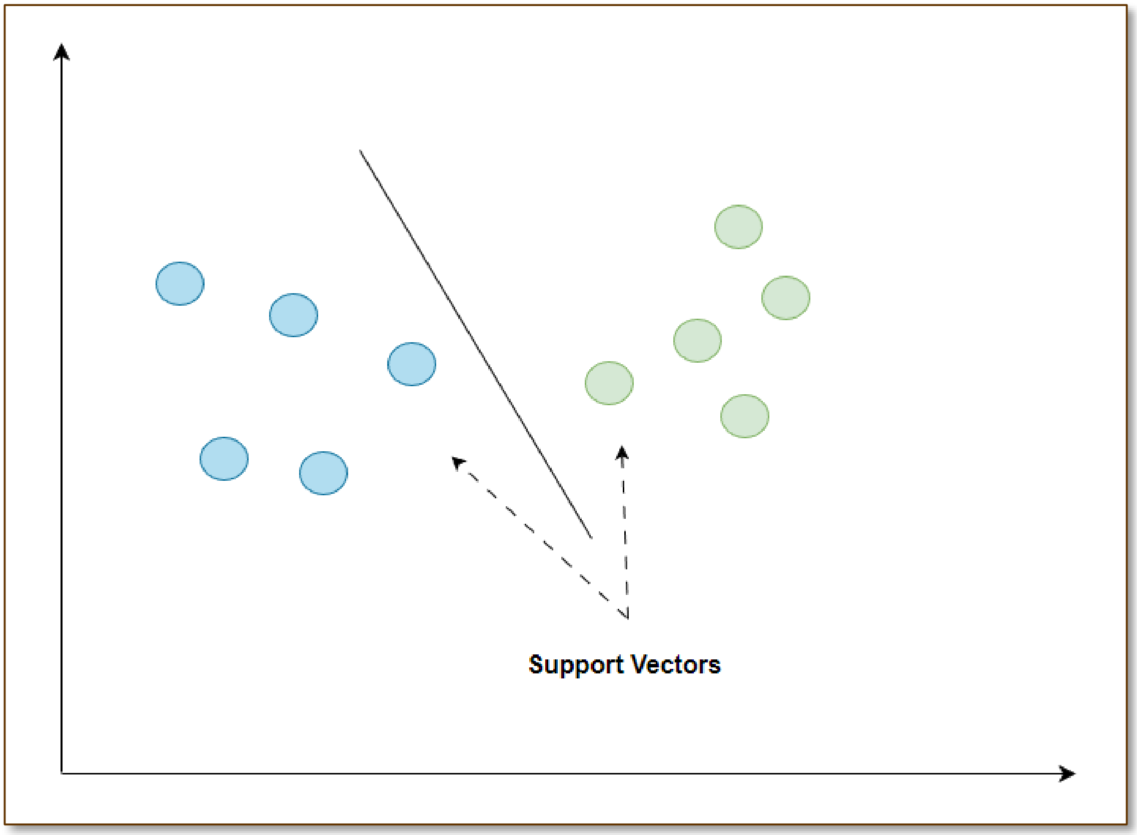
```
from sklearn.metrics import accuracy_score
print(accuracy_score(test_labels.preds))
0.951754385967
```

The result shows that the NaiveBayes classifier is **95.17%** accurate.

That was a machine learning classifier based on the *Naive Bayse Gaussian* model.

Support Vector Machine (SVM)

Basically, a Support vector machine (SVM) is a supervised machine learning algorithm that can be used for both regression and classification. The main concept of SVM is to plot each data item as a point in n-dimensional space with the value of each feature being the value of a particular coordinate. Here n would be the features we would have. Following is a simple graphical representation to understand the concept of SVM:



Vectors

In the above diagram, we have two features. Hence, we first need to plot these two variables in two-dimensional space where each point has two coordinates, called support vectors. The line splits the data into two different classified groups. This line would be the classifier.

Here, we are going to build an SVM classifier by using the scikit-learn and iris datasets. Sciktlearn libary has the **sklearn.svm** module and provides *sklearn.svm.svc* for classification. The SVM classifier to predict the class of the iris plant based on 4 features is shown below.

Dataset

We will use the iris dataset which contains 3 classes of 50 instances each, where each class refers to a type of iris plant. Each instance has four features namely sepal length, sepal width, petal length, and petal width. The SVM classifier to predict the class of the iris plant based on 4 features is shown below.

Kernel

Is a technique used by SVM. Basically, these are the functions that take low-dimensional input space and transform it into a higher-dimensional space. It converts non-separable problems to separable problems. The kernel function can be anyone among linear, polynomial, rbf, and sigmoid. In this example, we will use the linear kernel.

Let us now import the following packages:

```
import pandas as pd
import numpy as np
from sklearn import svm, datasets
import matplotlib.pyplot as plt
```

Now, load the input data:

```
iris = datasets.load_iris()
```

We are taking first two features:

```
x = iris.data [:, :2]
y = iris.target
```

We will plot support vector machine boundaries with original data. We are creating a mesh to the plot.

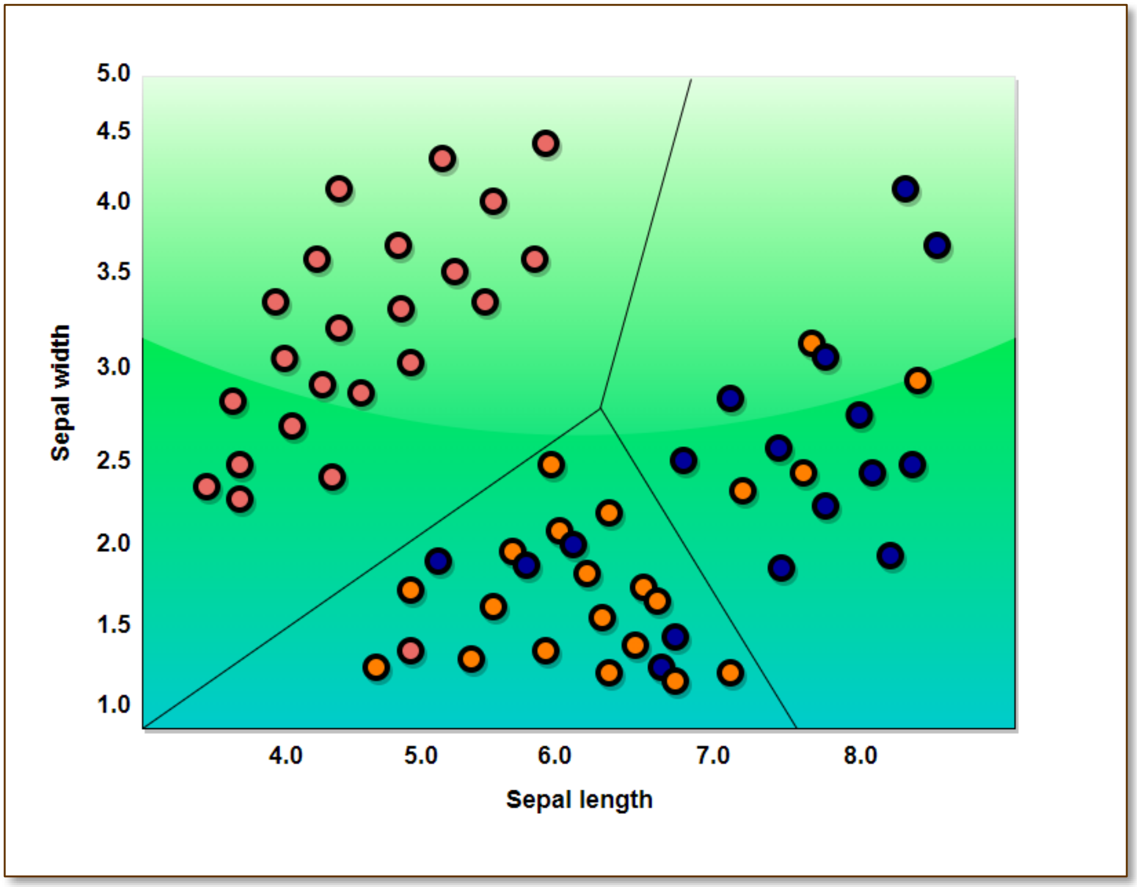
```
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1],max() + 1
h = (x_max / x_min)/100
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
np.arange(y_min, y_max, h))
X_plot = np.c_[xx.ravel(), yy.ravel()]
```

We need to give the value of the regularization parameter.

C = 1.0

We need to create the SVM classifier object.

```
Svc_classifier = svm_classifier.SVC(kernel='liner',
C=C, decision_function_shape = 'ovr').fit(X, y)
Z = svc_classifier.predict(X_plot)
Z = Z.reshape(xx.shape)
plt.figure(figsize = (15, 5))
plt.subplot(121)
plt.contourf(xx, yy, Z, cmap = plt.cm.tab10, alpha = 0.3)
plt.scatter(X[:, 0], X[:, 1], c = y, cmap = plt.cm.Set1)
plt.xlabel['Sepal length']
plt.ylabel['Sepal width']
plt.xlim(xx.min(), xx.max())
plt.title('SVC with linear kernel')
```



SVC with linear

5.4 Logistic Regression

Basically, the logistic regression model is one of the members of the supervised classification algorithm family. Logistic regression measures the relationship between dependent variables and independent variables by estimating the probabilities using a logistic function.

Here, if we talk about dependent and independent variables then the dependent variable is the target class variable we are going to predict and on the other side, the independent variables are the features we are going to use to predict the target class.

In logistic regression, estimating the probabilities means predicting the likelihood of the occurrence of the event. For example, the shop owner would like to predict the customer who entered the shop will buy the play station (for example) or not. There would be many features of the customer - *gender, age, etc*. which would be observed by the shopkeeper to predict the likelihood of occurrence, i.e., buying a play station or not. The logistic function is the sigmoid curve that is used to build the function with various parameters.

Prerequistes

Before building the classifier using logistic regression, we need to install the Tkinter package on our system, it can be installed from

```
https://docs.python.org/2/libary/thinter.html
```

Now, with the help of the code given below, we can create a classifier using logistic regression:

First, we will import some packages:

```
import numpy as np
from sklearn import linear_model
import matplolib.pyplot as plt
```

Now, we need to define the sample data which can be done as follows:

```
x = np.array([[2, 4.8], [2.9, 4.7], [2.5, 5], [3.2, 5.5], [6, 5], [7.6, 
4],
              [3.2, 0.9], [2.9, 1.9], [2.4, 3.5], [0.5, 3.4], [1, 4], 
[0.9, 5.9]])
y = np.array ([0, 0, 0, 1, 1, 1, 2, 2, 2, 3, 3, 3])
```

Next, we need to create the logistic regression classifier, which can be done as follows:

```
Classifier_LR = linear_model.logisticRegression(solver = 'liblinear', C = 75)
```

Last but not the least, we need to train this classifier:

```
Classifier_LR.fit(x, y)
```

Now, how we can visualize the output? It can be done by creating a function named **Logistic_visualize()** :

```
Def Logistic_visualize(Classifier_LR, X, y):
  min_x, max_x = X[:, 0].min() - 1.0, X[:, 0].max() + 1.0
  min_y, max_y = X[:, 1].min() - 1.0, X[:, 1].max() + 1.0
```

In the above line, we defined the minimum and maximum values X and Y to be used in mesh frid. In addition, we will define the step size for plotting the mesh grid.

```
mesh_step_size = 0.02
```

Let us define the mech grid of **X** and **Y** values as follows:

```
x_vals, y_vals = np.meshgrid(np.arrange(min_x), max_x, mesh_step_size),
                 np.arange(min_y, max_y, mesh_step_size)
```

With the help of following code, we can run the classifier on the mesh grid:

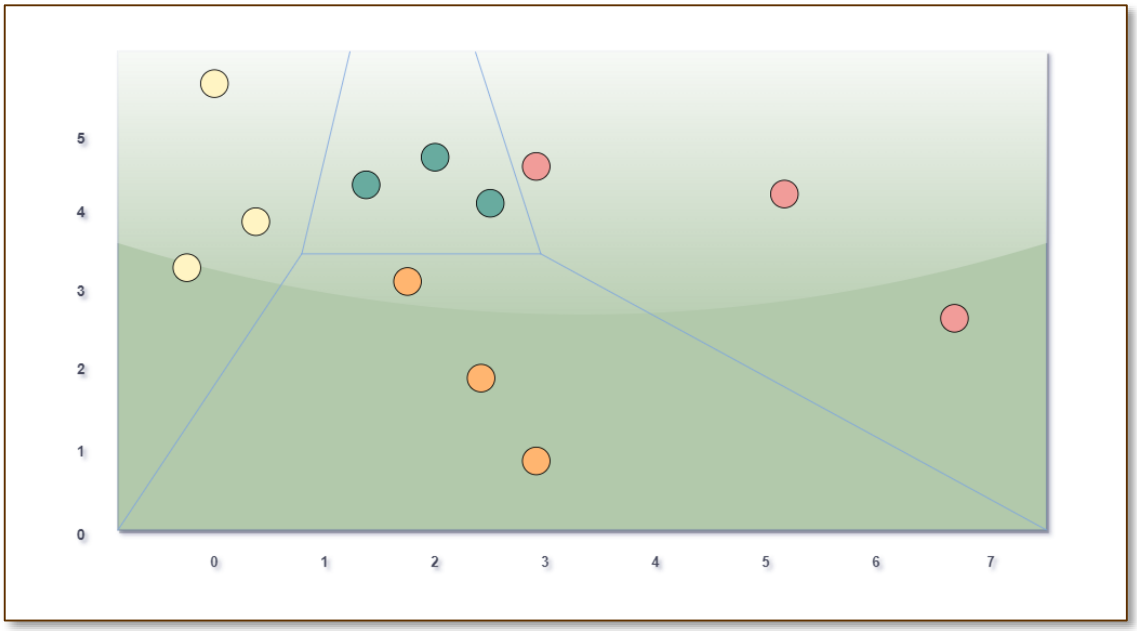
```
output = classifier.predict(np.c_[x_vals.ravel(), y_vals.ravel()])
output = output.reshape(x_vals.shape)
plt.figure()
plt.pcolermesh(x_vals, y_vals, output, cmap = plt.cm.gray)

plt.scatter(x[:, 0], X[:, 1], c = y, s = y, s = 75, edgecolors =
'black',
linewidth=1, cmap = plt.cm.Paired)
```

The following line of code will specify the boundaries of the plot:

```
plt.xlim(x_vals.min(), x_vals.max())
plt.ylim(_vals.min(), y_vals.max())
plt.xticks((np.arrange(int(X[:, 0].min() - 1), int(X[:, 0].max() + 1),
1.0)))
plt.yticks((np.arrange(int(X[:, 1].min() - 1), int(X[:, 1].max() + 1),
1.0)))
plt.show()
```

Now, after running the code we will get the following output, logistic regression classifier:



Prerequisites

5.5 Decision Tree Classifier

A decision tree is basically a binary tree flowchart where each node splits a group of observations according to some feature variable.

Here, we are building a Decision Tree classifier for predicting male or female. We will take a very small data set having 19 samples. These samples would consist of two features - *'height'* and *'length of hair'*.

Prerequisite

For building the following classifier, we need to install **pydotplus** and **graphviz**. Basically, graphviz is a tool for drawing graphics using dotfiles and **pydotplus** is a module for *Graphviz's Dot language*. It can be installed with the package manager or pip.

Now, we can build the decision tree classifier with the help of the following Python code:

To begin with, let us import some important libraries as follows:

```
import pydotplus
from sklearn.import tree
from sklearn.datasets import load_iris
from sklearn.metrics import classification_report
from sklearn.import cross_validation
import collections
```

Now, we need to provide the dataset as follows:

```
X = [[165, 19], [175 ,32], [136, 35], [174, 65], [141, 28], [176, 15],
[131, 32],
[166, 6], [128, 32], [179,10], [136, 34], [186, 2], [126, 25], [176,
28], [112, 38],
[169, 9], [171, 36], [116, 25], [196, 25]]

Y = ['Man', 'Woman', 'Woman', 'Man', 'Woman', 'Man', 'Woman', 'Man',
'Woman',
'Man', 'Woman', 'Man', 'Woman', 'Woman', 'Woman', 'Man', 'Woman',
'Woman', 'Man']
data_feature_names = ['height', 'length of hair']

X_train, X_test, Y_train, Y_test = cross_validation.train_test_split
(X, Y, test_size=0.40, random_state=5)
```

After providing the dataset, we need to fit the model which can be done as follows:

```
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X, Y)
```

Prediction can be made with the help of the following code:

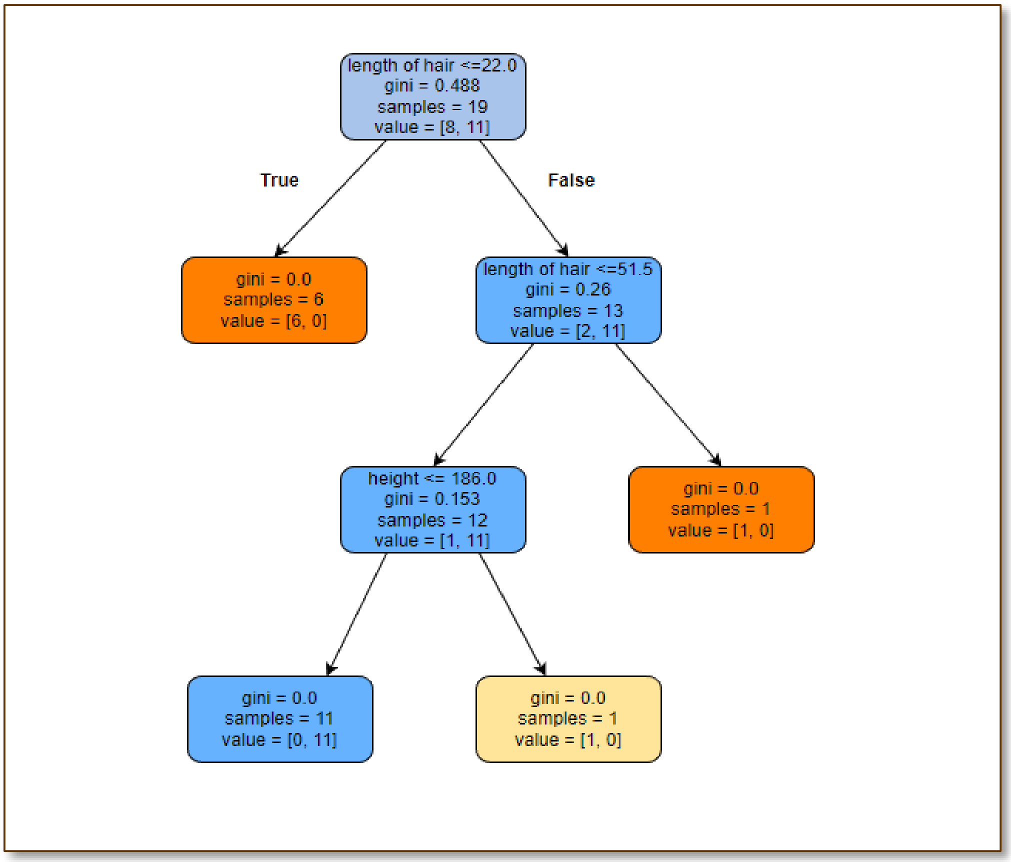
```
dot_data = tree.export_graphviz(clf, feature_names =
data_feature_names,
           out_file = None, filled = True, rounded = True)
graph = pydotplus.graph_from_dot_data(dot_data)
colors = ('orange', 'yellow')
edges = collections.defaultdict(list)

for edge in graph.get_edge_list():
edges [edge.get_source()].append(int(edge.get_destination()))

for edge in edges: edges[edge].sort()

for i in range(2):dest = graph.get_node(str(edges[edge][i]))[0]
dest.set_fillcolor(colors[i])
graph.write_png('Decisiontree16.png')
```

It will give the prediction for the above code as **['Woman']** and create the following decision tree:



Prediction model

We can change the values of features in the prediction to test it.

5.6 Random Forest Classifier

As we know that ensemble methods are the methods that combine machine learning models into a more powerful machine learning model. Random Forest, a collection of decision trees, is one of them. It is better than a single decision tree because while retraining the predictive powers it can reduce over-filtering by averaging the results. Here, we are going to implement the random forest model on the scikit learn cancer dataset.

Import the necessary packages:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_breast_cancer
cancer = load_breast.cancer()
import matplotlib.pyplot as plt
import numpy as np
```

Now, we need to provide the dataset which can be done as follows&minus

```
cancer = load_breast_cancer()
X_train, X_test, y_train,
y_test = train_test_split(cancer.data, cancer.target, random_state = 0)
```

After providing the dataset, we need to fit the model which can be done as follows:

```
forest = RandomForestClassifier(n_estimators = 50, random_state = 0)
forest.fit(X_train, y_train)
```

Now, get the accuracy on training as well as a testing subset: if we will increase the number of estimators then, the accuracy of the testing subset would be increased.

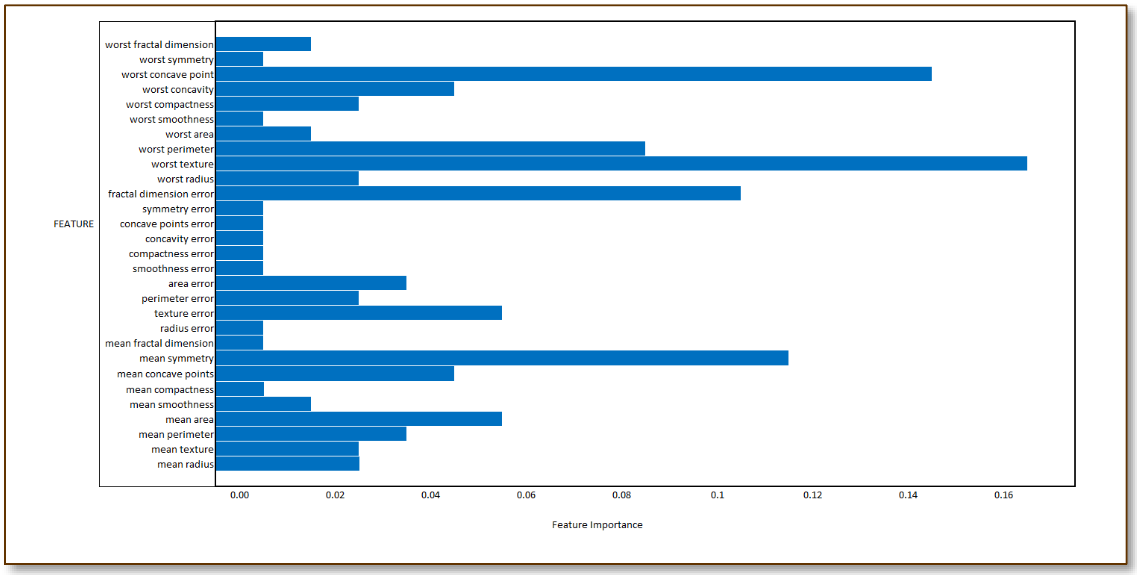
```
print('Accuracy on the training subset:(:.3f)',
format(forest.score(X_train, y_train)))
print('Accuracy on the training subset:(:.3f)',
format(forest.score(X_test, y_test)))
```

Output

```
Accuracy on the training subset:(:.3f) 1.0
Accuracy on the training subset:(:.3f) 0.965034965034965
```

Now, like the decision tree, the random forest has the **feature_importance** module which will provide a better view of feature weight than a decision tree. It can be plotted and visualized as follows:

```
n_features = cancer.data.shape[1]
plt.barh(range(n_features),forest.feature_importances_, align='center')
plt.yticks(np.arrange(n_features), cancer.feature_names)
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.show()
```



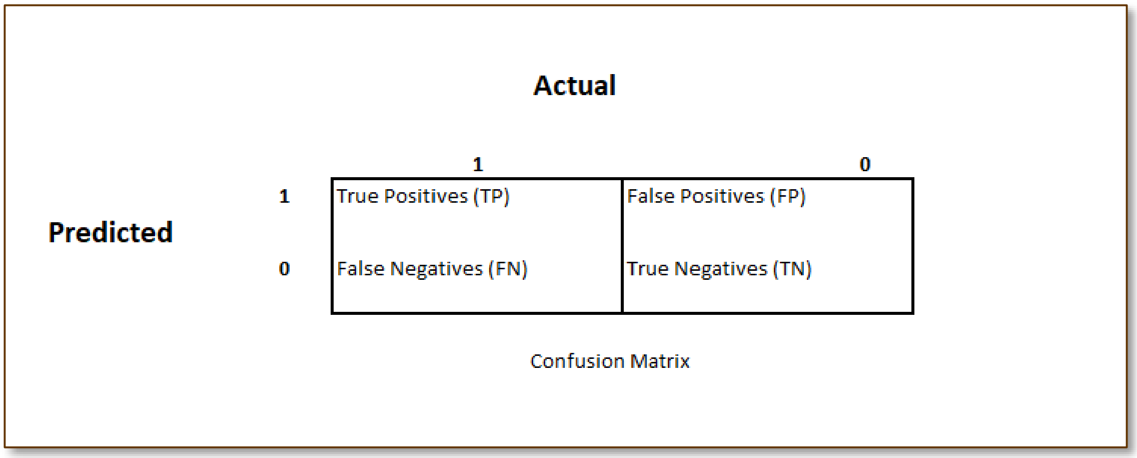
Output

5.7 Performance of a classifier

After implementing a machine learning algorithm, we need to find out how effective the model is. The criteria for measuring the effectiveness may be based on datasets and metrics. For evaluating different machine learning algorithms, we can use different performance metrics. For example, suppose a classifier is used to distinguish between images of different objects, we can use the classification performance metrics such as *average accuracy, AUC, etc*. In one or another sense, the metric we choose to evaluate our machine learning model is very important because the choice of metrics influences how the performance of a machine learning algorithm is measured and compared. Following are some of the metrics:

Confusion Matrix

Basically it is used for classification problems where the output can be of two or more types of classes. It is the easiest way to measure the performance of a classifier. A confusion matrix is basically a table with two dimensions namely *"Actual"* and *"Predicted"*. Both dimensions have *"True Positives (TP)", "True Negatives (TN)", "False Positives (FP)", "False Negatives (FN)"*.



Actual

Predicted		**1**	**0**
	1	True Positives (TP)	False Positives (FP)
	0	False Negatives (FN)	True Negatives (TN)

Confusion Matrix

Confusion Matrix

In the confusion matrix above, **1** is for the positive class and **0** is for the negative class.

Following are the terms associated with the Confusion matrix:

- **True Positives** - TPs are the cases when the actual class of data point was **1** and the predicted is also **1**.
- **True Negatives** - TNs are the cases when the actual class of the data point was **0** and the predicted is also **0**.
- **False Positives** - FPs are the cases when the actual class of data point was **0** and the predicted is also **1**.
- **False Negatives** - FNs are the cases when the actual class of the data point was **1** and the predicted is also **0**.

Accuracy

The confusion matrix itself is not a performance measure as such but almost all the performance matrices are based on the confusion matrix. One of them is accuracy. In classification problems, it may be defined as the number of correct predictions made by the model over all kinds of predictions made. The formula for calculating the accuracy is as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$$

Precision

It is mostly used in document retrievals. It may be defined as how many of the returned documents are correct. Following is the formula for calculating the precision:

$$Precision = \frac{TP}{TP+FP}$$

Recall or Sensitivity

It may be defined as how many of the positives do the model return. Following is the formula for calculating the recall/sensitivity of the model:

$$Recall = \frac{TP}{TP+FN}$$

Specificity

It may be defined as how many of the negatives the model return. It is exactly the opposite to recall. Following is the formula for calculating the specificity of the model:

$$Specificity = \frac{TN}{TN+FP}$$

5.8 Class Imbalance Problem

Class imbalance is the scenario where the number of observations belonging to one class is significantly lower than those belonging to the other classes. For example, the problem is prominent in the scenario where we need to identify *rare diseases, fraudulent transactions in banks, etc.*

Example of imbalanced classes

Let us consider an example of fraud detection data set to understand the concept of an imbalanced class:

```
Total observations = 5000
Fraudulent Observations = 50
Non-Fradulent Observations = 4950
Event Rate = 1%
```

Solution

Balancing the classes' acts as a solution to imbalanced classes. The main objective of balancing the classes is to either increase the frequency of the minority class or decrease the frequency of the majority class. Following are the approaches to solve the issue of imbalances classes:

Re-Sampling

Re-sampling is a series of methods used to reconstruct the sample data sets - both training sets and testing sets. Re-sampling is done to improve the accuracy of the model. Following are some re-sampling techniques:

- **Random Under-Sampling**: This technique aims to balance class distribution by randomly eliminating majority class examples. This is done until the majority and minority class instances are balanced out.

```
Total observations = 5000
Fraudulent Observations = 50
Non-Fradulent Observations = 4950
Event Rate = 1%
```

In this case, we are taking **10%** samples without replacement from the non-fraud instances and then combine them with the fraud instances:

Non-fraudulent, observations after random sampling = **10% of 4950 = 495**

Total observations after combining them with fraudulent observations = **50+495=545**

Hence now, the event rate for new dataset after under-sampling = **9%**

The main advantage of this technique is that it can reduce run time and improve storage. But on the other side, it can discard useful information while reducing the number of training data samples.

- **Random Over-Sampling**: This technique aims to balance class distribution by increasing the number of instances in the minority class by replacing them.

```
Total observations = 5000
Fraudulent Observations = 50
Non-Fradulent Observations = 4950
Event Rate = 1%
```

In case we are replacing 50 fraudulent observations 30 times then fraudulent observations after replicating the minority class observations would be 1500. And then the total observation in the new data after oversampling would be **4950+1500 = 6400**. Hence the event rate for the new data set would be **1500/6450 = 23%**

The main advantage of this method is that there would be no loss of useful information. But on the other hand, it has an increased chance of over-fitting because it replicates the minority class events.

5.9 Ensemble Techniques

This methodology basically is used to modify existing classification algorithms to make them appropriate for imbalanced data sets. In this approach, we construct several two-stage classifiers from the original data and then aggregate their predictions. A random forest classifier is an example of an ensemble-based classifier.

6 Regression

Is one of the most important statistical and machine-learning tools. We would not be wrong to say that the journey of machine learning starts from regression. It may be defined as the parametric technique that allows us to make decisions based on data by learning the relationship between input and output variables. Here, the output variables dependent on the input variables, are continuous-valued real numbers. In regression, the relationship between input and output variables matters and it helps us in understanding how the value of the output variable changes with the change of the input variable. Regression is frequently used for the prediction of *prices, economics, variations*, and so on.

6.1 Building Regressors in Python

In this section, we will learn how to build single as well as multivariable regressors.

Linear Regressor/Single Variable Regressor

Let us important a few required packages:

```
import numpy as np
from sklearn import linear_model
import sklearn.metrics as sm
import matplotlib.pyplot as plt
```

Now, we need to provide the input data and we have saved our data in the file named **linear.txt**

```
input = 'D:/ProgramData/linear.txt'
```

We need to load this data by using the **np.loadtxt** function.

```
input_data = np.loadtxt(input, delimiter=',')
X, y = input_data[:, :-1], input_data[:, -1]
```

The next step would be to train the model. Let us give training and testing samples.

```
training_samples = int(0.6 * len(X))
testing_samples = len(X) - num_training

X_train, y_train = X[:training_samples], y[:training_samples]

X_test, y_test = X[training_samples:], y[training_samples:]
```

Now, we need to create a linear regressor object.

```
reg_linear = linear_model.linearRegression()
```

Train the object with the training samples.

```
reg_linear.fit(X_train, y_train)
```

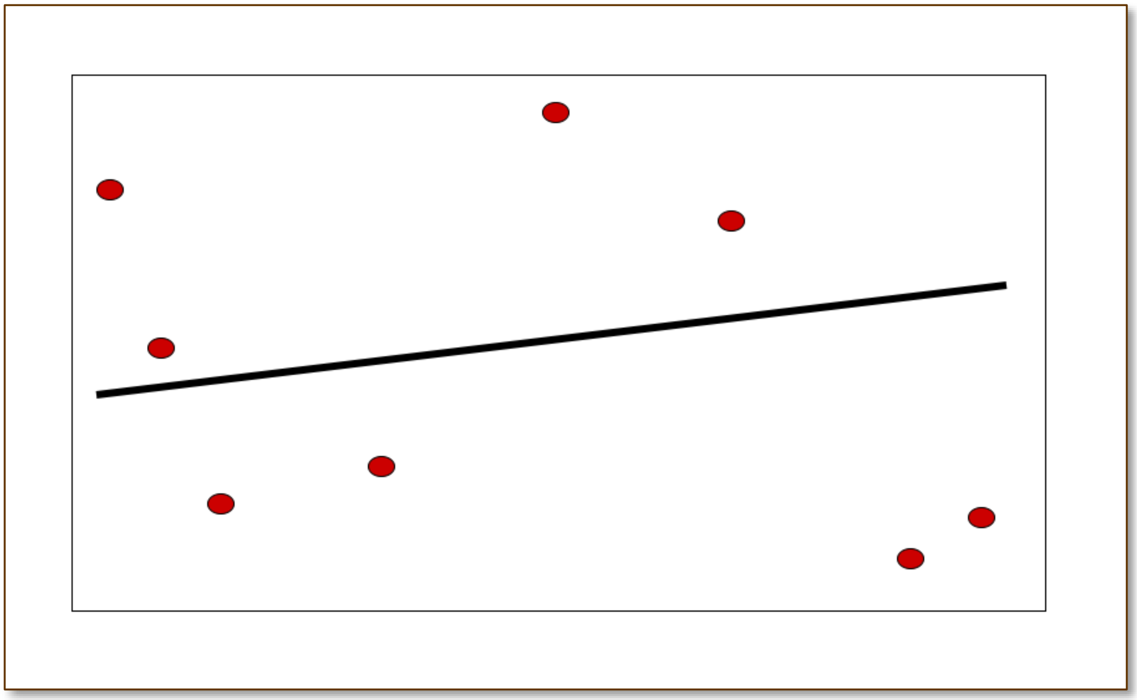
We need to do the prediction with the testing data.

```
y_test_pred = reg_linear.predict(X_test)
```

Now plot and visualize the data.

```
plt.scatter(X_test, y_test, color = 'red')
plt.plot(X_test, y_test_pred, color = 'black', linewidth = 2)
plt.xticks(())
plt.yticks(())
plt.show()
```

Output



Linear Regressor

Now, we can compute the performance of our liner regression as follows:

```
print("Performance of Linear regressor:")
print("Mean absolute error =", round(sm.mean_absolute_error(y_test, 
y_test_pred), 2))
print("Mean squared error =", round(sm.mean_sqared_error(y_test, 
y_test_pred), 2))
print("Median absolute error =", round(sm.median_absolute_error(y_test, 
y_test_pred), 2))
print("Explain variance score =", 
round(sm.explained_variance_score(y_test, y_test_pred), 2))
print("R2 score =", round(sm.r2_score(y_test, y_test_pred), 2))
```

Output

Performance of Linear Regressor:

```
Mean absolute error = 1.78
Mean squared error = 3.89
Median absolute error = 2.01
Explain variance score = -0.09
R2 score = -0.09
```

In the above code, we have used this small data. If you want a big dataset then you can use **sklearn.dataset** to import a bigger dataset.

```
2,4.82.9,4.72.5,53.2,5.56,57.6,43.2,0.92.9,1.92.4,
3.50.5,3.41,40.9,5.91.2,2.583.2,5.65.1,1.54.5,
1.22.3,6.32.1,2.8
```

Multivariable Regressor0

First, let us import a few required packages:

```
import numpy as np
from sklearn import linear_model
import sklearn.metrics as sm
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
```

Now, we need to provide the input data and we have saved our data in the file named **linear.txt**

```
input = 'D:/ProgramData/Mul_linear.txt'
```

7 Logic Programming

In this chapter, we will focus on logic programming and how it helps in Artificial Intelligence.

We already know that logic is the study of principles of correct reasoning or simple words it is the strudy of what comes after what. For example, if two statements are true then we can infer any third statement from them.

Concept

Logic Programming is the combination of two words, logic and programming Logic Programming is a programming paradigm in which the problems are expressed as facts and rules by program statements but within a system of formal logic. Just like other programming paradigms like *object-oriented, functional, declarative, procedural, etc*, it is also a particular way to approach programming.

7.1 How to Solve Problems with Logic Programming

Logic Programming uses facts and rules for solving the problem. That is why they are called the building blocks of Logic Programming. A goal needs to be specified for every program in logic programming. To understand how a problem can be solved in logic programming, we need to know about the building blocks - *Facts and Rules*.

Facts

Actually, every logic program needs facts to work with so that it can achieve the given goal. Facts basically are true statements about the program and data. For example, Delhi is the capital of India.

Rules

Actually, rules are the constraints that allow us to make conclusions about the problem domain. Rules basically written as logical clauses to express various facts. For example, if we are building any game then all the rules must be defined.

Rules are very important to solve any problem in Logic Programming. Rules are basically logical conclusions that can express the facts. Following is the syntax of rule:

```
A:-B1,B2,...,B[].
```

Here, **A** is the head, and **B1, B2, ... Bn** is the body.

For example: `ancestor(X,Y):-father(X,Y)`

```
ancestor(X,Z):-father(X,Y), ancestor(Y,Z).
```

- This can be read as, for every **X** and **Y**, if **X** is the father of **Y** and **Y** is an ancestor of **Z**, **X** is the ancestor of **Z**.
- For every **X** and **Y**, **X** is the ancestor of **Z**, if **X** is the father of **Y** and **Y** is an ancestor of **Z**.

7.2 Installing Useful Packages

For starting logic programming in Python, we need to install the following two packages.

Kanren

provides us with a way to simplify the way we made code for business logic. It lets us express logic in terms of rules and facts. The following command will help you install kanren:

```
pip install kanren
```

SymPy

Is a Python library for symbolic mathematics. It aims to become a full-featured computer algebra system (*CAS*) while keeping the code as simple as possible in order to be comprehensible and easily extensible. The following command will help you install SymPy:

```
pip install sympy
```

7.3 Example of Logic Programming

Following are some examples that can be solved by logic programming.

Matching mathematical expressions

Actually we can find unknown values by using logic programming in a very effective way. The following Python code will help you match a mathematical expression.

Consider importing the following packages first:

```
from kanren import run, var, fact
from kanren.assoccomm import eq_assoccomm as eq
from kanren.assoccomm import commutative, associative
```

We need to define the mathematical operations which we are going to use:

```
add = 'add'
mul = 'mul'
```

Both addition and multiplication are communicative processes. Hence, we need to specify it and this can be done as follows:

```
fact(commutative, mul)
fact(commutative, add)
fact(associative, mul)
fact(associative, add)
```

It is compulsory to define variables; this can be done as follows:

```
a, b = var('a'), var ('b')
```

We need to match the expression with the original pattern. We have the following original pattern, which is basically `(5+a)*b`

```
Original_pattern = (mul, (add, 5, a), b)
```

We have the following two expressions to match with the original pattern:

```
exp1 = (mul, 2, (add, 3, 1))
exp2 = (add, 5, (mul, 8,1))
```

Output can be printed with the following command:

```
print(run(0, (a,b), eq(original_pattern, exp1)))
print(run(0, (a,b), eq(original_pattern, exp2)))
```

After running this code, we will get the following output:

```
((3, 2))
()
```

The first output represents the values for **a** and **b**. The first expression matched the original pattern and returned the values for **a** and **b** but the second expression did not match the original pattern hence nothing has been returned.

7.4 Checking for Prime Numbers

With the help of logic programming, we can find prime numbers from a list of numbers and can also generate prime numbers. The Python code given below will find the prime number from a list of numbers and will also generate the first 10 prime numbers.

Let us first consider importing the following packages:

```
from kanren import isvar, run, membero
from kanren.core import success, fail, goaleval, condeseq, eq, var
from sympy.ntheory.generate import prime, isprime
import itertools as it
```

Now, we will define a function called **prime_check** which will check the prime numbers based on the given numbers as data.

```
def prime_check(x):
if isvar(x):
   return condeseq([(eq, x, p)] for p in map(prime, it.count(1)))
else:
   return success if isprime(x) else fail
```

Now, we need to declare a variable which will be used

```
x = var()
print((set(run(0,x,(membero,x,(12,14,15,19,20,21,22,23,29,30,41,44,52,6
2,65,85)),(prime_check,x)))))
print((run(10,x,prime_check(X))))
```

The output of the code will be as follows:

```
{19, 23, 29, 41}
(2, 3, 5, 7, 11, 13, 17, 19, 23, 29)
```

7.5 Solving Puzzles

Logic programming can be used to solve many problems like *8-puzzles, Zebra puzzle, Sudoku, N-queen, etc*. Here we are talking about an example of a variant of Zebra puzzle which is as follows:

```
There are five houses.
The English man lives in the red house.
The Swede has a dog.
The Dane drinks tea.
The greenhouse is immediately to the left of the white house.
They drink coffee in the greenhouse.
The man who smokes Pall Mall has birds.
In the yellow house, they smoke Dunhill.
In the middle house, they drink milk.
The Norwegian lives in the first house.
The man who smokes Blend lives in the house next to the house with
cats.
In a house next to the house where they have a horse, they smoke
Dunhill.
The man who smokes Blue Master drinks beer.
The German smokes Prince.
The Norwegian lives next to the blue house.
They drink water in a house next to the house where they smoke Blend.
```

We are solving the question of **who owns zebra** with help of Python.

Let us import the necessary packages.

```
from kanren import *
from kanren.core import lall
import time
```

Now, we need to define two functions - **left()** and **next()** to check whose house is left or next to who’s house:

```
def left(q, p, list):
    return membero((q, p), zip(list, list[1:]))
    def next(q, , p, list):
    return conde([left(q, p, list)], [left(p,q, lists)])
```

Now, we will declare a variable house as follows:

```
houses = var()
```

We need to define the rules with the help of lall package as follows:

There are 5 houses:

```
rules_zebraproblem = lall(
  (eq, (var(), var(), var(), var(), var()), houses),

  (membero, ('Enhlishman', var(), var(), var(), 'red'), houses),
  (membero, ('Swedie', var(), var(), 'dog', var()), houses),
  (membero, ('Dane', var(), 'tea', var(), var()), 'houses),
  (left,(var(), var(), var(), var(), 'green'),
  (var(), var(), var(), var(), 'green'),
  (membero,(var(), var(), 'coffee', var(), 'green'), houses),
  (membero,(var(), 'Pall Mall', var(), 'birds', var()), houses),
  (eq,(var(), var(), (var(), var(), 'milk', var(), var()), var(),
var()), houses),
  (eq,(('Norwegian', var(), var(), var(), var()), var(), var(), var(),
var()), houses),
  (next,(var(), 'Blend', var(), var(), var()),
  (var(), var(), var(), 'cats', var()), houses),
  (next,(var(), 'Dunhill', var(), var(), var()),
  (var(), var(), var(), 'horse', var()), houses),
  (membero, (var(), 'Blue Master', 'beer', var(), var()), houses),
  (membero,('German', 'Prince', var(), var(), var()), houses),
  (next,('Norwegian', var(), var(), var(), var()),
  (var(), var(), var(), var(), 'blue'), houses),
  (next,(var(), 'Blend', var(), var(), var()),
  (var(), var(), 'water', var(), var()), houses),
  (membero,(var(), var(), var(), 'zebra', var()), houses)
)
```

Now, run the solver with the preceding constraints:

```
solutions = run(0, houses, rules_zebraproblem)
```

With the help of the following code, we can extract the output from the solver:

```
output_zebra = [house for house in solutions [0] if 'zebra' in house][0][0]
```

The followng code will help print the solution:

```
print ('\n' + output_zebra + 'owns zebra.')
```

The output of the above code would be as follows:

```
German owns zebra.
```

8 Unsupervised Learning Clustering

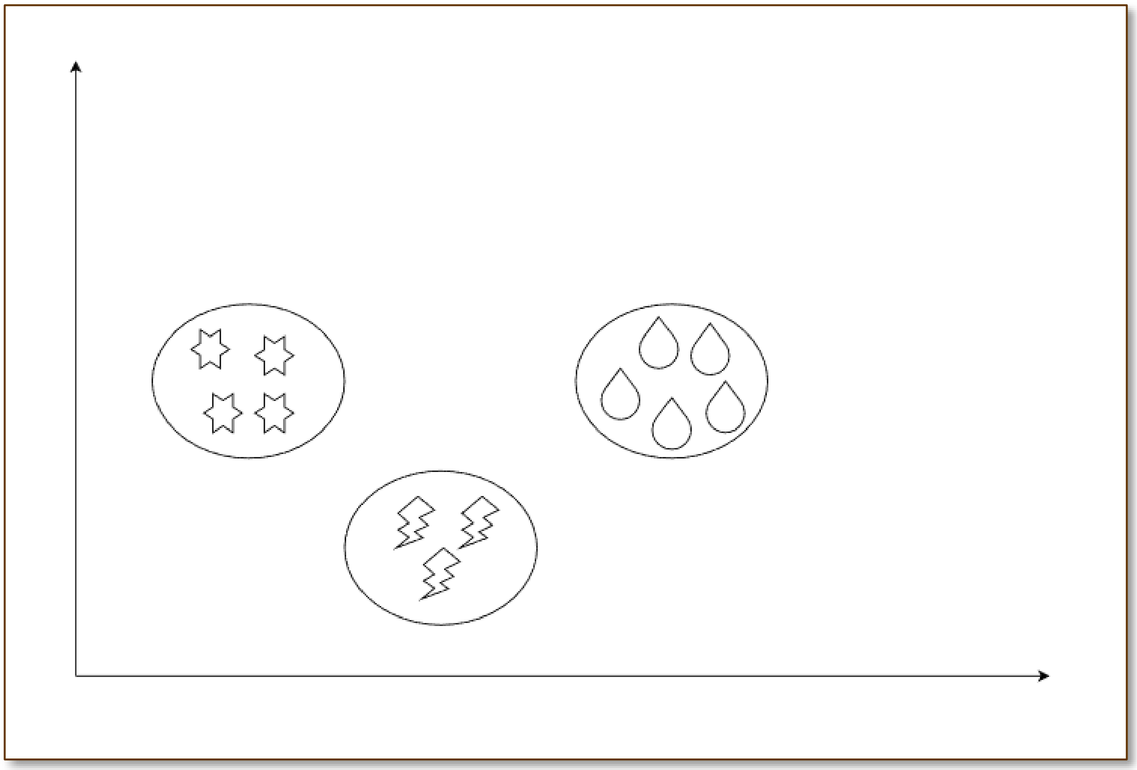
Unsupervised machine learning algorithms do not have any supervisor to provide any sort of guidance. That is why they are closely aligned with what some call true artificial intelligence.

In unsupervised learning, there would be no correct answer and no teacher for guidance. ALgorithms need to discover interesting patterns in data for learning.

8.1 What is Clustering?

Basically, it is a type of unsupervised learning method and a common technique for statistical data analysis used in many fields. Clustering mainly is a task of dividing the set of observations into subsets, called clusters, in such a way that observations in the same cluster are similar in one sense and they are dissimilar to the observations in other clusters. In simple words, we can say that the main goal of clustering is to group the data on the basis of similarity and dissimilarity.

For example, the following diagram shows similar kinds of data in different clusters:



Clustering

8.2 Algorithms for Clustering the Data

Following are a few common algorithms for clustering the data.

K-Means algorithm

K-means clustering algorithm is one of the well-known algorithms for clustering data. We need to assume that the number of clusters is already known. This is also called flat clustering. It is an iterative clustering algorithm. The steps given below need to be followed for this algorithm:

Step 1 - We need to specify the desired number of K subgroups.

Step 2 - Fix the number of clusters and randomly assign each data point to a cluster. Or in other words, we need to classify our data based on the number of clusters.

In this step, cluster centroids should be computed.

As this is an iterative algorithm, we need to update the locations of *K centroids* with every iteration until we find the global optima or in other words, the centroids reach their optimal locations.

The following code will help in implementing the *K-means clustering algorithm* in Python. We are going to use the **Scikit-learn** module.

Let us import the necessary packages:

```
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import numpy as np
from sklearn.cluster import KMeans
```

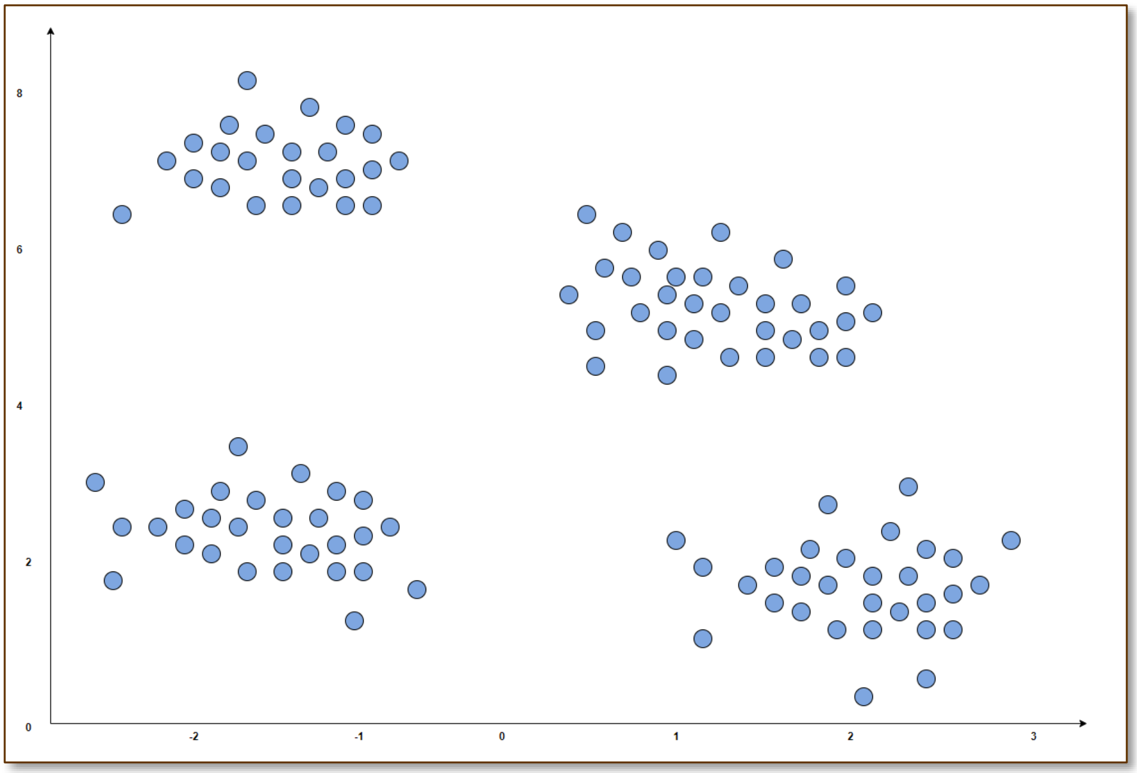
The following line of code will help in generating the two-dimensional dataset, containing four blobs, by using **make_blob** from **sklearn.dataset** package.

```
from sklearn.datasets.samples_generator import make_blobs

X, y_true = make_blobs(n_samples = 500, centers = 4,
            cluster_std = 0.40, random_state = 0 )
```

We can visualize the dataset by using the following code:

```
plt.scatter(X[:, 0], X[:,1], s = 50);
plt.show()
```



KMean

Here, we are initializing kmeans to be the KMeans algorithm, with the required parameter of how many clusters(n_clusters).

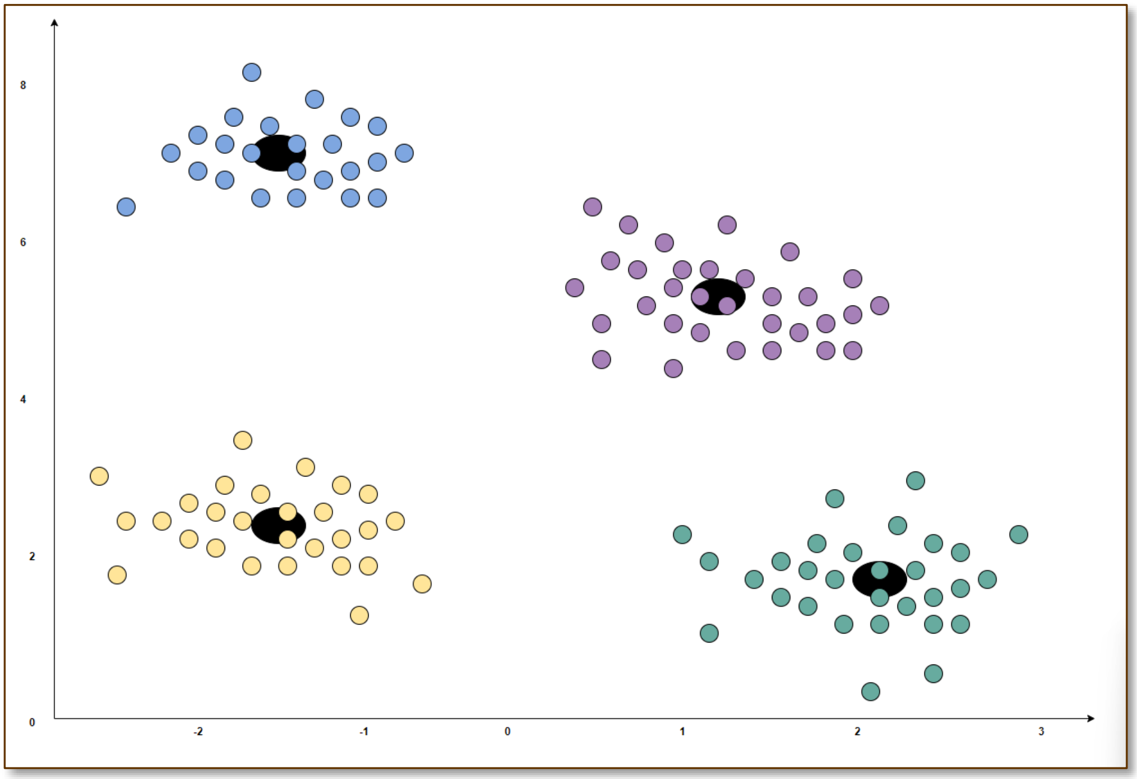
We need to train the K-means model with the input data.

```
kmeans.fit(X)
y_kmeans = kmeans.predict(X)
plt.scatter(X[:, 0], X[:, 1], c = y_kmeans, s = 50, cmap = 'viridis')


centers = kmeans.cluster_centers_
```

The code given below will help us plot and visualize the machine's findings based on our data, and the fitment according to the number of clusters that are to be found.

```
plt.scatter(centers[:, 0], centers[:, 1], c = 'black', s = 200, alpha = 0.5);
plt.show()
```



Machine Findings

Mean Shift Algorithm

It is another popular and powerful clustering algorithm used in unsupervised learning. It does not make any assumptions hence it is a non-parametric algorithm. It is also called hierarchical clustering or mean shift cluster analysis. Following would be the basic steps of this algorithm:

- First of all, we need to start with the data points assigned to a cluster of their own.
- Now, it computes the centroids and updates the location of new centroids.
- By repeating this process, we move closer to the peak of the cluster i.e. towards the region of higher density.
- This algorithm stops at the stage where centroids do not move anymore.

With the help of the following code, we are implementing the Mean Shift clustering algorithm in Python. We are going to use the Scikit-learn module.

Let us import the necessary packages:

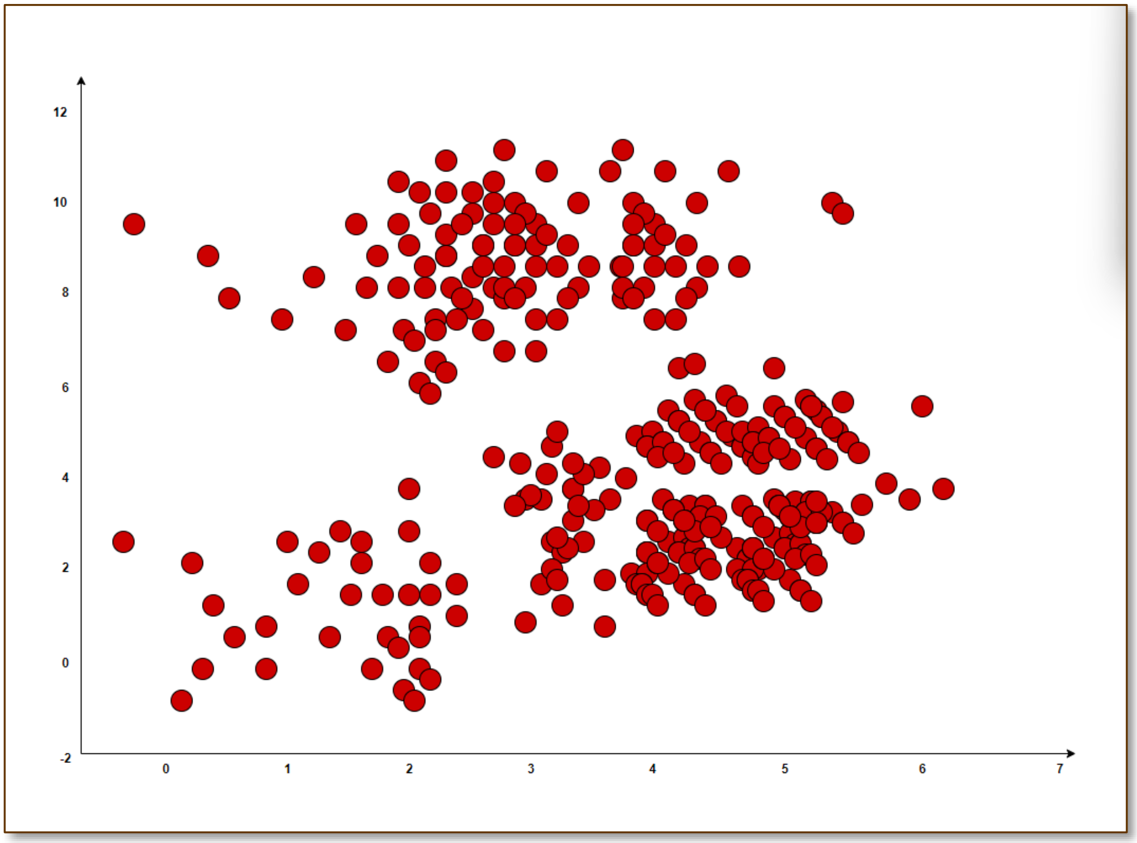
```
import numpy as np
from sklearn.cluster import MeanShift
import matplotlib.pyplot as plt
from matplotlib import style
style.use("ggplot")
```

The following code will help in generating the two-dimensional dataset, containing four blobs, by using **make_blob** from **sklearn.dataset** package.

```
from sklearn.datasets.simples_generator import make_blobs
```

We can visualize the dataset with the following code

```
center = [[2,2],[4,5],[3,10]]
X, _ = make_blobs(n_samples = 500, centers = centers, cluster_std = 1)
plt.scatter(X[:,0], X[:,1])
plt.show()
```



Mean Shift

Now, we need to train the Mean Shift cluster model with the input data.

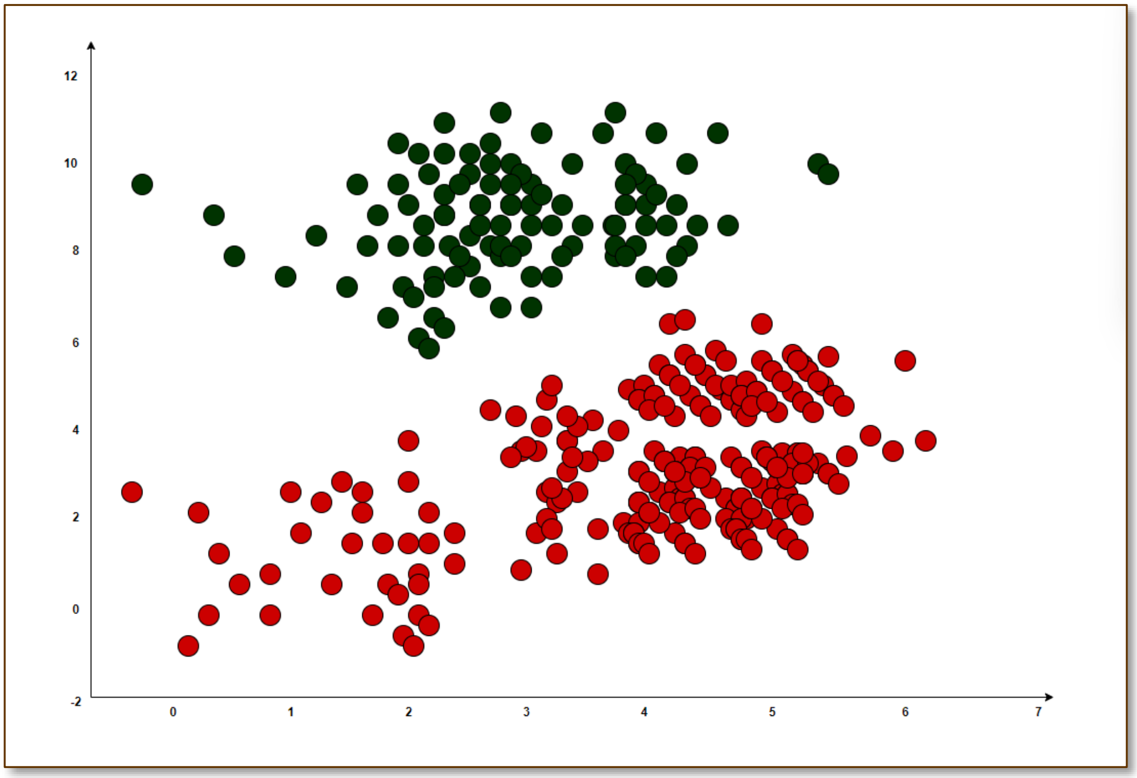
```
ms = MeanShift()
ms.fit(X)
labels = ms.labels_
cluster_centers = ms.cluster_centers_
```

The following code will print the cluster centers and the expected number of the cluster as per the input data:

```
print(cluster_centers)
n_clusters_ = len(np.unique(labels))
print("Estimated cluster:", n_clusters_)
[[3.230005036 3.84771893]
[ 3.02057451 9.88928991]]
Estimated cluster: 2
```

The code given below will help plot and visualize the machine's findings based on our data, and the fitment according to the number of clusters that are to be found.

```
colors = 10*['r.,','g.','b.','c.','k.','y.','m.']
    for i in range(len(X)):
    plt.plot(X[i][0], X[i][1], colors(labels[i]), markersize = 10)
plt.scatter(cluster_centers[:, 0], cluster_centers[:,1],
    marker = "x",color = 'k', s = 150, linewidths = 5, zorder = 10)
plt.show()
```



Visualize Mean Shift

8.3 Measuring the Clusterin Performance

The real-world data is not naturally organized into a number of distinctive clusters. Due to this reason, it is not easy to visualize and draw interferences. That is why we need to measure the clustering performance as well as its quality. It can be done with the help of silhouette analysis.

Silhouette Analysis

This method can be used to check the quality of clustering by measuring the distance between the clusters. Basically, it provides a way to assess the parameters like a number of clusters by giving a silhouette score. This score is a metric that measures how close each point in one cluster is to the points in the neighboring clusters.

Analysis of silhouette score

This method can be used to check the quality of clustering by measuring the distance between the clusters. Basically, it provides a way to assess the parameters like a number of clusters by giving a silhouette score. This score is a metric that measures how close each point in one cluster is to the point in the neighboring clusters.

Analysis of silhouette score

The score has a range of **[-1, 1]**. Following is the analysis of the score:

- **Score of +1**: A score near **+1** indicates that the sample is far away from the neighboring cluster,
- **Score of 0**: Score **0** indicates that the sample is on or very close to the decision boundary between two neighboring clusters.
- **Score of -1**: Negative score indicates that the samples have been assigned to the wrong clusters.

8.4 Calculating Silhouette Score

In this section, we will learn how to calculate the silhouette score.

Silhouette score can be calculated by using the formula:

```
$$silhouette score =\frac{\left (p-q\right)}{max\left (p,q\right)}$$
```

Here, **p** is the mean distance to the points in the nearest cluster that the data point is not a part of. And, **q** is the mean intra-cluster distance to all the points in its own cluster.

For finding the optimal number of clusters, we need to run the clustering algorithm again by importing the **metrics** module from the **sklearn** package. In the following example, we will run the K-means clustering algorithm to find the optimal number of clusters:

Import the necessary packages as shown:

```
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import numpy as np
from sklearn.cluster import KMMeans
```

With the help of the following code, we will generate the two-dimensional dataset, containing four blobs, by using **make_blob** from **sklearn.dataset** package.

```
from sklearn.datasets.samples_generator import make_blobs
X, y_true = make_blobs(n_samples = 500, centers = 4, cluster_std =
0.50, random_state = 0)
```

Initialize the variables as shown:

```
score = []
values = np.arange(2, 10)
```

We need to iterate the K-means model through all the values and also need to train it with the input data.

```
for num_clusters in values:
kmeans = KMeans(init = 'k-means++', n_clusters = num_clusters, n_init =
10)
kmeans.fit(X)
```

Now estimate the silhouette score for the current clustering model using the Euclidean distance metric:

```
score = metrics.silhouette_score(X, kmeans.labels_,
metric = 'euclidean', sample_size = len(X))
```

The following line of code will help in displaying the number of clusters as well as the Silhouette score.

```
print("\nNumber of clusters =", num_clusters)
print("Solhouette score =", score)
scores.append(score)
```

You will receive the following output:

```
Number of clusters = 9
Silhouette score = 0.340391138371

num_clusters = np.argmax(scores) + values[0]
print('\nOptimal number of clusters =', num_clusters)
```

Now, the output for the optimal number of clusters would be as follows:

```
Optimal number of clusters = 2
```

8.5 Finding Nearest Neighbors

If we want to build recommender systems such as a movie recommender system then we need to understand the concept of finding the nearest neighbors. It is because the recommender system utilizes the concept of nearest neighbors.

The **concept of finding the nearest neighbors** may be defined as the process of finding the closest point to the input point from the given dataset. The main use of this KNN) is K-nearest neighbors) the algorithm is to build a classification system that classifies a data point on the proximity of the input data point to various classes.

The Python code given below helps in finding the K-nearest neighbors of a given data set:

Import the necessary packages as shown below. Here, we are using the **NearestNeighbors** module from the **sklearn** package:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import NearestNeighbors
```

Let us now define the input data:

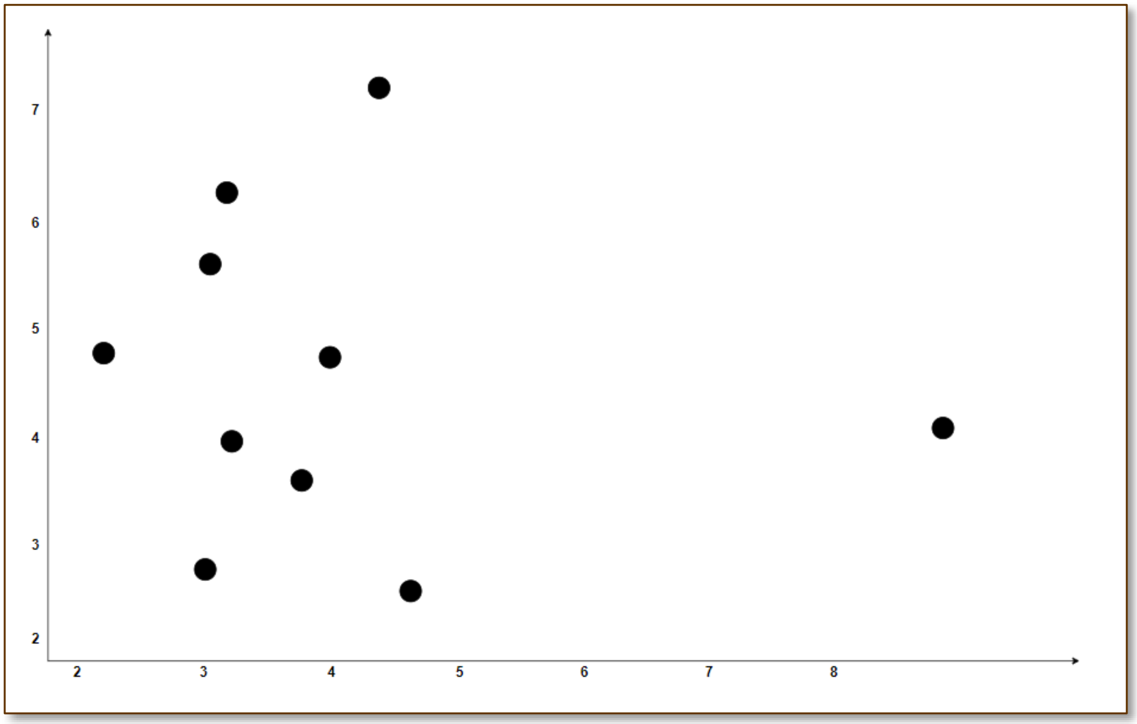
```
A = np.array([[3.1, 2.3], [2.3, 4.2], [3.9, 3.5], [3.7, 6.4], [4.8, 1.9]
              [8.3, 3.1], [5.2, 7.5], [4.8, 4.7], [3.5, 5.1], [4.4, 2.9],])
```

Now, we need to define the nearest neighbors:

k = 3

We also need to give the test data from which the nearest neighbors is to be found:

```
plt.figure()
plt.title('Input data')
plt.scatter(A[:,0], A[:,1], marker = 'o', s = 100, color = 'black)
```



Finding Nearest Neighbors

Now, we need to build the K Nearest Neighbor. The object also needs to be trained:

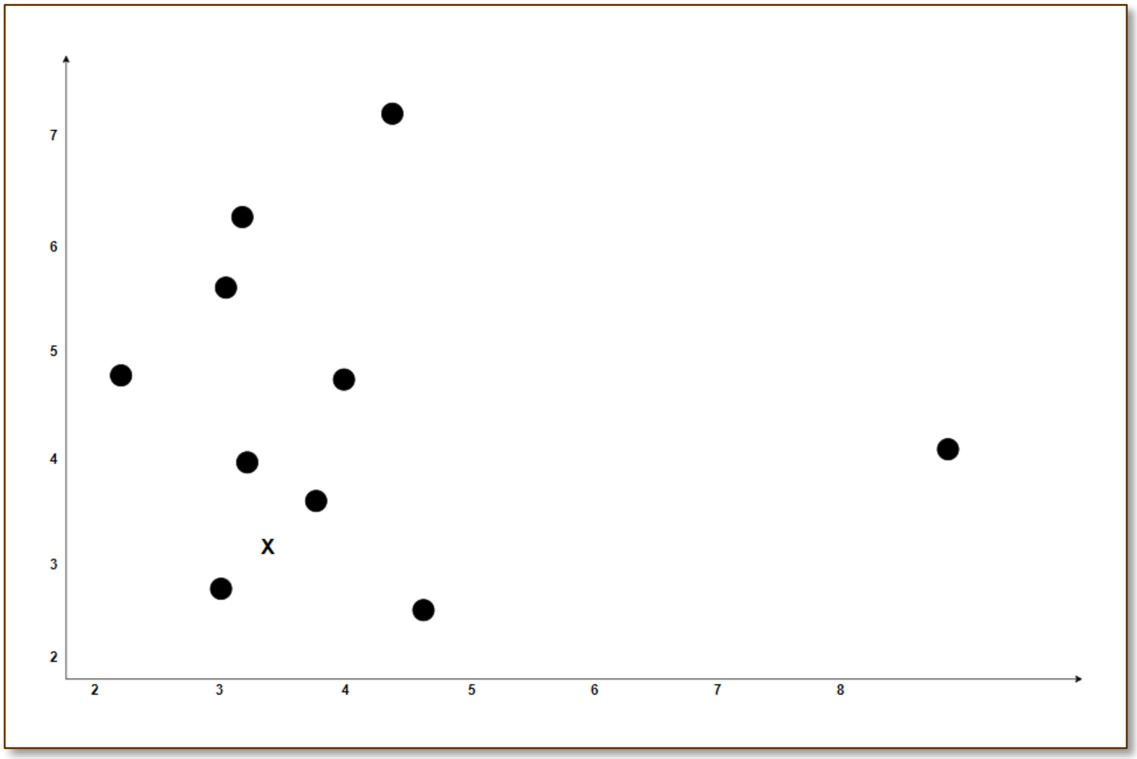
```
knn_model = NearestNeighbors(n_neighbors = k, algorithm =
'auto').fit(X)
distances, indices = knn_model.kneighbors([test_data])
```

Now, we can print the K nearest neighbors as follows:

```
print("\nK Nearest Neighbors:")
for rank, index in enumerate(indices[0][:k], start = 1):
        print(str(rank) + "is", A[index])
```

We can visualize the nearest neighbors along with the test data point:

```
plt.figure()
plt.title('Nearest neighbors')
plt.scatter(A[:, 0], X[:, 1], marker = '0', s = 100, color = 'k')
plt.scatter(A[indices][0][:][:, 0], A[indices][0][:][:, 1],
        marker = 'o', s = 250, color = 'k', facecolors = 'none')
plt.scatter(test_data[0], test_data[1],
        marker = 'x', s = 100, color = 'k')
plt.show()
```



Finding Nearest Neighbors

Output

K Nearest Neighbors

```
1 is [3.1 2.3]
2 is [3.9 3.5]
3 is [4.4 2.9]
```

8.6 K-Nearest Neighbors Classifier

A *K-Nearest Neighbors (KNN) classifier* is a classification model that uses the nearest neighbors algorithm to classify a given data point. We have implemented the *KNN algorithm* in the last section, now we are going to build a *KNN classifier* using that algorithm.

Concept of KNN Classifier

The basic concept of *K-nearest neighbor classification* is to find a predefined number, i.e., the *'k'* - of training samples closest in distance to a new sample, which has to be classified. New samples will get their label from the neighbors themselves. The *KNN classifiers* have a fixed user-defined constant for the number of neighbors which has to be determined. For the distance, standard Euclidean distance is the most common choice. The *KNN Classifier* works directly on the learned samples rather than creating the rules for learning. The *KNN algorithm* is among the simplest of all machine learning algorithms. It has been quite successful in a large number of classification and regression problems, for example, character recognition or image analysis.

Example

We are building a *KNN classifier* to recognize digits. For this, we will use the *MNIST dataset*. We will write this code in *Jupyter Notebook*.

Import the necessary packages as shown below.

Here we are using the **KNeighborsClassifier** module from the **sklearn.neighbors** package:

```
from sklearn.datasets import *
import panda as pd
%matplotlib.inline
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt
import numpy as np
```

The following code will display the image of the digit to verify what image we have to test:

```
def Image_display(i):
    plt.imshow(digit['images'][i], cmap = 'Greys_r')
    plt.show()
```

Now, we need to load the *MNIST dataset*. Actually, there is a total of 1797 images but we are using the first 1600 images as training samples and the remaining 197 would be kept for testing purposes.

```
digit = load_digits()
digit_d = pd.DataFrame(digit['data'][0: 1600])
```

Now, on displaying the images we can see the output as follows:

```
Image_display(0)
```

Image_display(0) Image of **0** is displayed as follows:

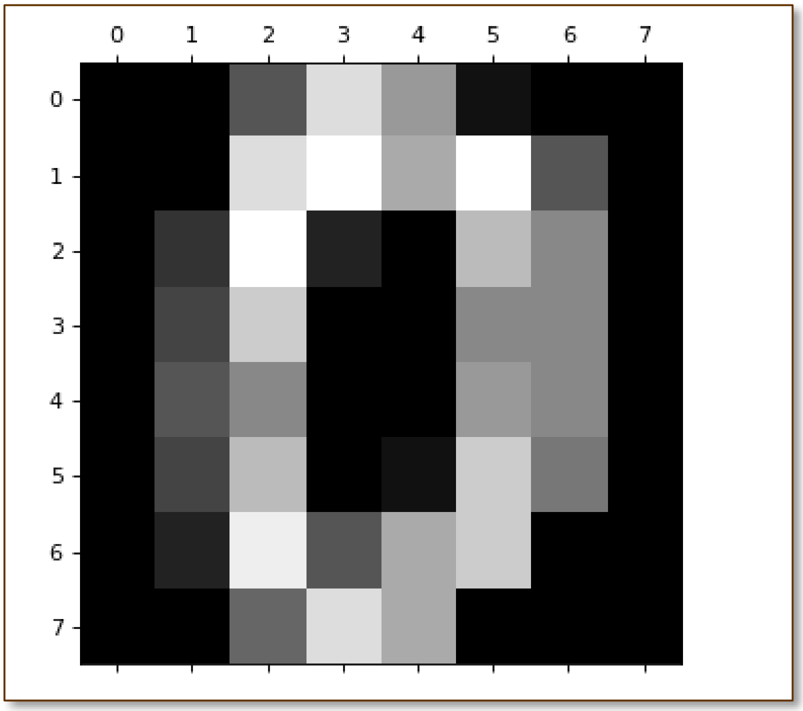


Image display - 0

Image_display(9) Image of **9** is displayed as follows:

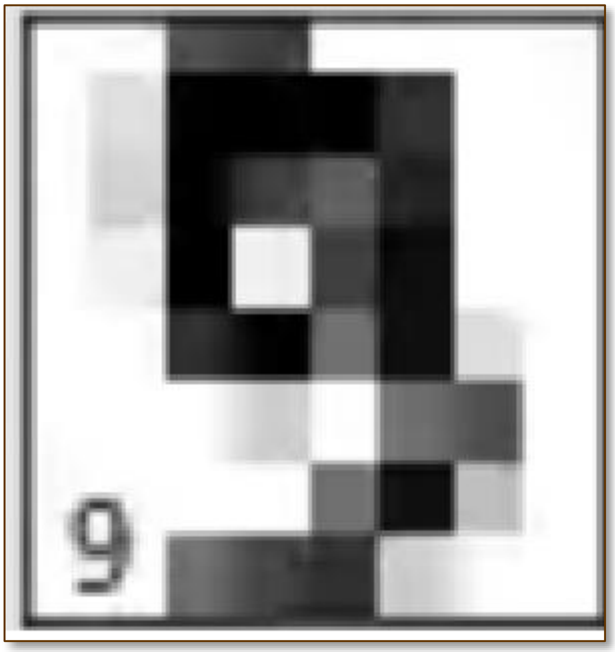


Image display - 9

digit_keys() Now, we need to create the training and testing data set and supply testing data set to the *KNN classifiers*.

```
train_x = digit['data'][:1600]
train_y = digit['target'][:1600]
KNN = KNeighborsClassifier(20)
KNN.fit(train_x, train_y)
```

The following output will create the K nearest neighbor classifier constructor:

```
KNeighborsClassifier(algorithm = 'auto', leaf_size = 30, metric =
'minkowski',
    metric_params = None, n_jobs = 1, n_neighbors = 20, p = 2,
    weights = 'uniform')
```

We need to create the testing sample by providing any arbitrary number greater than 1600, which were the training samples.

```
test = np.array(digit['data'][1725])
test1 = test.reshape(1, -1)
Image_display(1725)
```

Image_display(6) Image of **6** is displayed as follows:

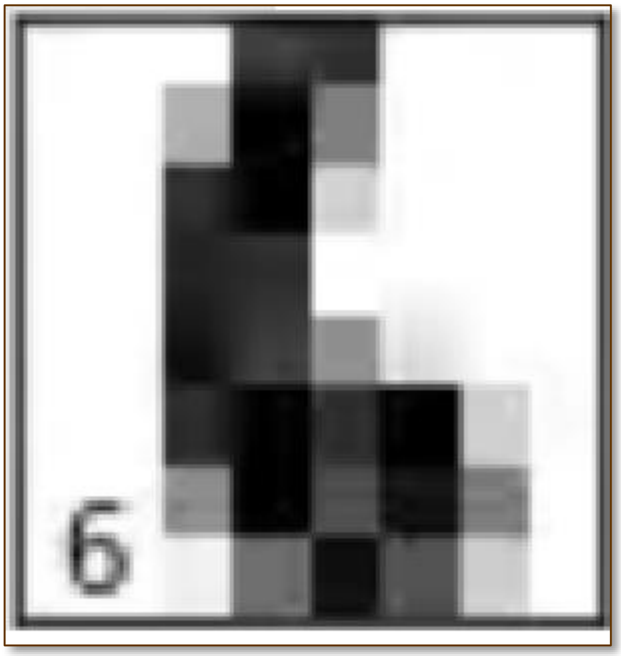


Image display - 6

Now we predict the test data as follows:

```
KNN.predict(test1)
```

The above code will generate the following output:

```
array([6])
```

Now, consider the following:

```
digit['target_names']
```

The above code will generate the following output:

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

9 Natural Language Processing

NPL refer to AI method of communicating with intelligent systems using a natural language such as English.

Processing of Natural Language is required when you want an intelligent system like a robot to perform as per your instructions, when you want to hear decisions from a dialogue-based clinical expert system, etc.

The field of NLP involves making computers perform useful tasks with the natural languages humans use. The input and output of an NPL system can be

- Speech
- Written Text

9.1 Components of NLP

In this section, we will learn about the different components of NLP. There are two components of NLP. The components are described below:

Natural Language Understanding (NLU)

It involves the following tasks:

- Mapping the given input in natural language into useful representations.
- Analyzing different aspects of the language.

Natural Language Generation (NLG)

It is the process of producing meaningful phrases and sentences in the form of natural language from some internal representation it involves

- **Text planning**: This includes retrieving the relevant content from the knowledge base.
- **Sentence planning**: This includes choosing the required words, forming meaningful phrases, and setting the tone of the sentence.
- **Text Realization**: This is mapping sentence plan into sentence structure.

9.2 Difficulties in NLU

The NLU is very rich in form and structure, however, it is ambiguous. There can be different levels of ambiguity:

Lexical ambiguity: It is at a very primitive level such as the word level. For example, treating the word *broad* as a noun or verb?

Syntax level ambiguity: A sentence can be parsed in different ways. For example, *"He lifted the beetle with a red cap."* - Did he use the cap to lift the beetle or he lifted a beetle that had a red cap?

Referential ambiguity: Referring to something using pronouns. For example, *Rima went to Gauri. She said, "I am tired."* - Exactly who is tired?

9.3 NPL Terminology

Let us now see a few important terms in the NLP terminology.

- **Phonology**: It is the study of organizing sound systematically.
- **Morphology**: It is a study of the construction of words from primitive meaningful units.
- **Morpheme**: It is a primitive unit of meaning in a language.
- **Syntax**: It refers to arranging words to make a sentence. It also involves determining words to make a sentence. It also involves determining the structural role of words in the sentence and in phrases.
- **Semantics**: It is concerned with the meaning of words and how to combine words into meaningful phrases and sentences.
- **Pragmatics**: It deals with using and understanding sentences in a different situation and how the interpretation of the sentence is affected.
- **Discourse**: It deals with how the immediately preceding sentence can affect the interpretation of the next sentence.
- **World Knowledge**: It includes general knowledge about the world.

9.4 Steps in NLP

This section shows the different steps in NLP:

Lexical Analysis

It involves identifying and analyzing the structure of words. The Lexicon of a language means the collection of words and phrases in a language. Lexical analysis is dividing the whole chunk of text into paragraphs, sentences, and words.

Syntactic Analysis (Parsing)

It involves the analysis of words in the sentence for grammar and arranging words in a manner that shows the relationship among the words. A sentence such as *A school goes to boy* is rejected by the English syntactic analyzer.

Semantic Analysis

It draws the exact meaning or the dictionary meaning from the text. The text is checked for meaningfulness. It is done by mapping syntactic structures and objects in the task domain. The semantic analyzer disregards sentences such as *hot ice cream*.

Discourse Integration

The meaning of any sentence depends upon the meaning of the sentence just before it. In addition, it also brings about the meaning of the immediately succeeding sentence.

Pragmatic Analysis

During this, what was said is re-interpreted on what it actually meant. It involves deriving those aspects of language which require real-world knowledge.

10 NLTK Package

In this chapter, we will learn how to get started with the Natural Language Toolkit Package.

Prerequisite: If we want to build an application with Natural Language processing then the change in context makes it most difficult. The context factor influences how the machine understands a particular sentence. Hence, we need to develop Natural language applications by using machine learning approaches so that machines can also understand the way a human can understand the context.

To build such applications we will use a Python package called NLTK (*Natural Language Toolkit Package*).

10.1 Importing NLTK

We need to install NLTK before using it. It can be installed with the help of the following command:

```
pip install nltk
```

Now after installing the NLTK package, we need to import it through the python command prompt. We can import it by writing the following command on the Python command prompt:

```
>>> import nltk
```

10.2 Downloading NLTK's Data

Now after importing NLTK, we need to download the required data. It can be done with the help of the following command on the Python command prompt:

```
>>> nltk.download()
```

10.3 Installing Other Necessary Packages

For building natural language processing applications by using NLTK, we need to install the necessary packages. The packages are as follows:

gensim

It is a robust semantic modeling library that is useful for many applications. We can install it by executing the following command:

```
pip install gensim
```

pattern

It is used to make **gensim** package work properly. We can install it by executing the following command:

```
pip install pattern
```

10.4 Concept of Tokenization, Stemming, and Lemmatization

In this section, we will understand what is tokenization, stemming, and lemmatization

Tokenization

It may be defined as the process of breaking the given text i.e. the character sequence into smaller units called tokens. The tokens may be words, numbers, or punctuation marks. It is also called word segmentation. Following is a simple example of tokenization:

- **Input**: Mango, banana, pineapple, and apple all are fruits.
- **Output**:

```
Mango    Banana   Pineap   and      Apple    all      are      fruits
                  ple
```

The process of breaking the given text can be done with the help of locating the word boundaries. The ending of a word and the beginning of a new word are called word boundaries. The writing system and the typographical structure of the words influence the boundaries.

In the Python NLTK module, we have different packages related to tokenization which we can use to divide the text into tokens as per our requirements. Some of the packages are as follows:

sent_tokenize package

As the name suggests, this package will divide the input text into sentences. We can import this package with the help of the following Python code:

```
from nltk.tokenize import sent_tokenize
```

word_tokenize package

This package divides the input text into words. We can import this package with the help of the following Python code:

```
from nltk.tokenize import word_tokenize
```

WordPunctTokenizer package

This package divides the input text into words as well as the punctuation marks. We can import this package with the help of the following Python code:

```
from nltk.tokenize import WordPuncttokenizer
```

Stemming

While working with words, we come across a lot of variations due to grammatical reasons. The concept of variations here means that we have to deal with different forms of the same words like *democracy*, *democratic*, and *democratization*. It is very necessary for machines to understand that these different words have the same base form. In this way, it would be useful to extract the base forms of the words while we are analyzing the text.

We can achieve this by stemming. In this way, we can say that stemming is the heuristic process of extracting the base forms of words by chopping off the ends of words.

In the Python NLTK module, we have different packages related to stemming. These packages can be used to get the base forms of words. These packages use algorithms. Some of the packages are as follows:

PorterStemmer package

This Python package uses Porter's algorithm to extract the base form. We can import this package with the help of the following Python code:

```
from nltk.stem.porter import PorterStemmer
```

For example, if we will give the word *writing* as the input to this stemmer then we will get the word *write* after stemming.

LancasterStemmer package This Python package will use Lancaster's algorithm to extract the base form. We can import this package with the help of the following Python code:

```
from nltk.stem.lancaster import LancasterStemmer
```

For example, if we will give the word *writing* as the input to this stemmer then we will get the word *write* after stemming.

SnowballStemmer package This Python package will use snowball's algorithm to extract the base form. We can import this package with the help of the following Python code:

```
from nltk.stem.snowball import SnowballStemmer
```

For example, if we will give the word *writing* as the input to this stemmer then we will get the word *write* after stemming.

All of these algorithms have a different levels of strictness. If we compare these three stemmers then the Porter stemmers is the least strict and Lancaster is the strictest. Snowball stemmer is good to use in terms of speed as well as strictness.

Lemmatization We can also extract the base form of words by lemmatization. It basically does this task with the use of a vocabulary and morphological analysis of words, normally aiming to remove inflectional endings only. This kind of base form of any word is called a lemma.

The main difference between stemming and lemmatization is the use of vocabulary and morphological analysis of the words. Another difference is that stemming most commonly collapses derivationally related words whereas lemmatization commonly only collapses the different inflectional forms of a lemma. For example, if we provide the word saw as the input word then stemming might return the word 's' but lemmatization would attempt to return the word either see or saw depending on whether the use of token was a verb or a noun.

In the Python NLTK module, we have the following package related to the lemmatization process which we can use to get the base forms of words.

WordNetLemmatizer package This Python package will extract the base form of the word depending on whether it is used as a noun or as a verb. We can import this package with the help of the following Python code:

```
from nltk.stem import WordNetLemmatizer
```

10.5 Chunking: Dividing Data into Chunks

It is one of the important processes in natural language processing. The main job of chunking is to identify the parts of speech and short phrases like noun phrases. We have already studied the process of tokenization, and the creation of tokens. In other words, chunking will show us the structure of the sentence.

In the following section, we will learn about the different types of Chunking.

Types of chunking

There are two types of chunking. The types are as follows:

Chunking up In this process of *chunking, the object, things, etc*. move towards being more general and the language gets more abstract. They are more chances of agreement. In this process, we zoom out. For example, if we will chunk up the question "*for what purpose cars are?*" We may get the answer "*transport*".

Chunking down In this process of *chunking, the object, things, etc.* move towards being more specific and the language gets more penetrated. The deeper structure would be examined in chunking down. In this process, we zoom in. For example, if we chunk down the question *"Tell specifically about a car?"*. We will get smaller pieces of information about the car.

Example In this example, we will do Noun-Phrases chunking, a category of chunking in which we will find the noun phrases chunks in the sentence, by using the NLTK module in Python:

Follow these steps in python for implementing noun phrase chunking

Step 1: In this step, we need to define the grammar for chunking. It would consist of the rules which we need to follow.

Step 2: In this step, we need to create a chunk parser. It would parse the grammar and give the output.

Step 3: In this last step, the output is produced in a tree format.

Let us import the necessary NLTK package as follows:

```
import nltk
```

Now, we need to define the sentence. Here, **DT** means the determinant, **VBP** means the verb, **JJ** means the adjective, **IN** means the preposition and **NN** means the noun.

```
sentence = [("a", "DT"),("clever","JJ"),("fox","NN"),("was","VBP"),
            ("jumping","VBP"),("over","IN"),("the","DT"),("wall","NN")]
```

Now, we need to give the grammar. Here, we will give the grammar in the form of the regular expression.

```
grammar = "NP:{<DT>?<JJ>*<NN>}"
```

We need to define a parser that will parse the grammar.

```
parser_chunking = nltk.RegexParser(grammar)
```

The parser parses the sentence as follows:

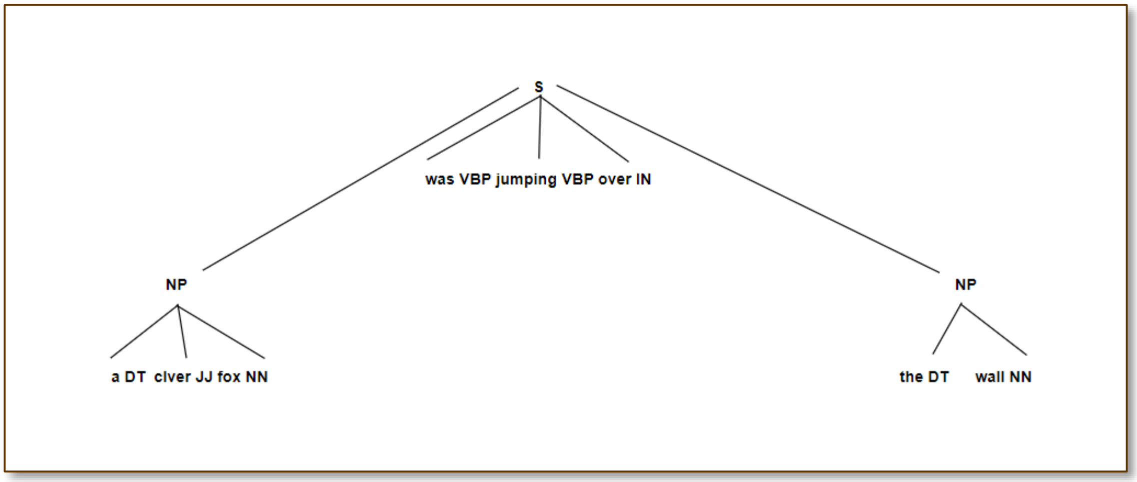
```
parser_chunking.parse(sentence)
```

Next, we need to get the output. The output is generated in the simple variable called **output_chunk**.

```
Output_chunk = parser_chunking.parse(sentence)
```

Upon execution of the following code, we can draw our output in the form of a tree.

```
output.draw()
```



Chunking Down

10.6Bag of Word (BoW) Model

Bag of Word (BoW), a model in natural language processing, is basically used to extract the features from the text so that the text can be used in modeling such that in machine learning algorithms.

Now the question arises that why we need to extract the features from the text. It is because machine learning algorithms cannot work with raw data and they need numeric data so that they can extract meaningful information from it. The conversion of text data into numeric data is called feature extraction or feature encoding.

How it works

This is a very simple approach for extracting the features from the text. Suppose we have a text document and we want to convert it into numeric data or say want to extract the features out of it then first of all this model extracts a vocabulary from all the words in the document. Then by using a document term matrix, it will build a model. In this way, *BoW* represents the document as a bag of words only. Any information about the order or structure of words in the document is discarded.

Concept of document term matrix

The *BoW algorithm* builds a model by using the document term matrix. As the name suggests, the document term matrix is the matrix of various word counts that occur in the document. With the help of this matrix, the text document can be represented as a weighted combination of various words. By setting the threshold and choosing the words that are more meaningful, we can build a histogram of all the words in the documents that can be used as a feature vector. Following is an example to understand the concept of document term matrix:

Example Suppose we have the following two sentences:

- **Sentence 1**: We are using the Bag of Words, model.
- **Sentence 2**: The bag of Words model is used for extracting the features.

Now, by considering these two sentences, we have the following 13 distinct words:

- we
- are
- using
- the
- bag
- of
- words
- model
- is
- used
- for
- extracting
- features

Now, we need to build a histogram for each sentence by using the word count in each sentence:

- **Sentence 1**: `[1,1,1,1,1,1,1,1,0,0,0,0,0]`
- **Sentence 2**: `[0,0,0,1,1,1,1,1,1,1,1,1,1]`

In this way, we have the feature vectors that have been extracted. Each feature vector is 13-dimensional because we have 13 distinct words.

10.7 Concept of the Statistics

The concept of the statistics is called *TermFrequency-Inverse Document Frequency (tf-idf)*. Every word is important in the document. The statistics help us understand the importance of every word.

Term Frequency(tf)

It is the measure of how frequently each word appears in a document. It can be obtained by dividing the count of each word by the total number of words in a given document.

Inverse Document Frequency(idf)

It is the measure of how unique a word is to this document in the given set of documents. For calculating idf and formulating a distinctive feature vector, we need to reduce the weights of commonly occurring words like the and weight up the rare words.

10.8 Building a Bag of Words Model in NLTK

In this section, we will define a collection of strings by using *Count/Vectorizer* to create vectors from these sentences.

Let us import the necessary package:

```
from sklearn.feature_extraction.text import CountVectorizer
```

Now define the set of sentences.

```
Sentences = ['We are using the Bag of Word model', 'Bag of Word model
is
              used for extracting the features.']

vectorizer_count = CountVectorizer()

features_text = vectorizer.fit_transform(Sentences).todense()

print(vectorizer.vocabulary_)
```

The above program generates the output as shown below. It shows that we have 13 distinct words in the above two sentences:

```
{'we': 11, 'are': 0, 'using': 10, 'the': 8, 'bag': 1, 'of': 7
'word': 12, 'model': 6, 'is': 5, 'used': 9, 'for': 4,
'extracting': 2, 'features': 3}
```

These are the feature vectors (text to numeric form) which can be used for machine learning.

10.9 Solving Problems

In this section, we will solve a few related problems.

Category Prediction

In a set of documents, not only the words but the category of the world is also important, in which category of text a particular word fails. For example, we want to predict whether a given sentence belongs to the category email, news, sports, computer, etc. In the following example, we are going to use tf-idf to formulate a feature vector to find the category of documents. We will use the data from 20 newsgroup datasets of sklearn.

We need to import the necessary packages:

```
from sklearn.datasets import fetch_20newsgroup
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import CountVectorizer
```

Define the category map. We are using five different categories named *Religion, Autos, Sports, Electronics, and Space*.

```
category_map = {'talk.religion.misc":'Religion','rec.autos''Autos',
                'rec.sport.hockey': 'Hookey', 'sci.electronics' :
'Electronics', 'sci.space' :'Space'}
```

Create the training set:

```
traning_data = fetch_20newsgroups(subset = 'train'
              categories = category_map.keys(), shuffle = True,
random_state = 5)
```

Build a count vectorizer and extract the term counts:

```
vectorizer_count = CountVectorizer()
train_tc = vectorizer_count.fit_transform(training_data.data)
print("\nDimensions of training data:", train_tc.shape)
```

The *tf-idf* transformer is created as follows:

```
tfidf = TfidTransformer()
train_tfidf = tfidf.fit_transform(train_tc)
```

Now, define the test data:

```
Input_data = [
      'Discovery was a space shuttle',
      'Hindu, Christian, Sikh all are religions',
      'We must have to drive safely',
      'Puck is a disk made of rubber',
      'Television, Microwave, Refrigerated all use electricity'
]
```

The above data will help us train a Multinomial Naive Bayes classifier:

```
classifier = MultinomialNB().fit(train_tfidf, traning_data.target)
```

Transform the input data using the count vectorizer:

```
input_tc = vectorizer_count.transform(input_data)
```

Now, we will transform the vectorized data using the tfidf transformer:

```
input_tfidf = tfidf.transform(input_tc)
```

We will predict the output categories:

```
predictions = classifier.predict(input_tfidf)
```

The output is generated as follows:

```
for sent, category in zip(input_data, predictions):
    print('\nInput Data:', sent, '\n Category:', \
         category_map[training_data.target_names[category]])
```

The category predictor generates the following output:

```
Dimensions of training data: (2755, 39297)

Input Data: Discovery was space shuttle
Category: Space

Input Data: Hindu, Christian, Sikh all are religions
Category: Religion

Input Data: We must have to drive safely
Category: Autos

Input Data: Puck is a disk made of rubber
Category: Hockey

Input Data: Television, Microwave, Refrigerated all uses electricity
Group: Electronics
```

Gender Finder

In this problem statement, a classifier would be trained to find the gender (*male or female*) by providing the names. We need to use a heuristic to construct a feature vector and train the classifier. We will be using the labeled data from the scikit-learn package. Following is the Python code to build a gender finder:

Let us import the necessary package:

```
import random

from nltk.import NaiveBayesClassifier
from nltk.classify import accuracy as nltk_accuracy
from ntlk.corpus import names
```

Now we need to extract the last N letters from the input word. These letters will act as features:

```
def extract_features(word, N = 2):
        last_n_letters = word[-N:]
        return {'feature': last_n_letters.lover()}

if __name ==' __main__';
```

Create the training data using labeled names (*male as well as female*) available in NLTK:

```
male_list = [(name, 'male') for name in main.words('male.txt')]
female_list = [(name, 'female') for name in names.words('female.txt')]
data = (male_list + female_list)

random.seed(5)
random.shuffle(data)
```

Now, test data will be created as follows:

```
namesInput = ['Rajesh', 'Gaurav', 'Swati', 'Shubiha']
```

Define the number of samples used for train and test with the following code

```
train_sample = int(0.8 * len(data))
```

Now, we need to iterate through different lengths so that the accuracy can be compared:

```
for i in range(1, 6):
    print('\nNumber of end letters: ', i)
    features = [(extract_features(n, i), gender) for (n, gender) in
data]
    train_data, test_data = features[:train_sample],
features[train_sample:]
    classifier = NaiveByesClassifier.train(train_data)
```

The accuracy of the classifier can be computed as follows:

```
accuracy_classifier = round(100 * nltk_accuracy(classifier, test_data),
2)
  print('Accuracy = ' + str(accuracy_classifier) + '&')
```

Now, we can predit the output:

```
for name in nameInput:
  print(name, '==>',
classifier.classifier.classify(extract_features(name, i)))
```

The above program will generate the following output:

```
Number of end letters: 1
Accuracy = 74.7%
Rajesh -> female
Gaurav -> male
Swati -> female
Shubha -> female

Number of end letters: 2
Accuracy = 78.79%
Rajesh -> male
Gaurav -> male
Swati -> female
Shubha -> female

Number of end letters: 3
Accuracy = 77.22%
Rajesh -> male
Gaurav -> female
Swati -> female
Shubha -> female

Number of end letters: 4
Accuracy = 69.98%
Rajesh -> female
Gaurav -> female
Swati -> female
Shubha -> female

Number of end letters: 5
Accuracy = 64.63%
Rajesh -> female
Gaurav -> female
Swati -> female
Shubha -> female
```

In the above output, we can see that accuracy in maximum number of end letters are two and it is decreasing as the number of end letters are increasing.

10.10 Topic Modeling: Identifying Patterns in Text Data

We know that generally documents are grouped into topics. Sometimes we need to identify the patterns in a text that correspond to a particular topic. The technique of doing this is called topic modeling is a technique to uncover abstract themes or hidden structures in a given set of documents.

We can use the topic modeling technique in the following scenarios:

Text Classification

With the help of topic modeling, classification can be improved because it groups similar words together rather than using each word separately as a feature.

Recommender Systems

With the help of topic modeling, we can build recommender systems by using similarity measures.

10.11 Algorithms for Topic Modeling

Topic modeling can be implemented by using algorithms. The algorithms are as follows:

Latent Dirichlet Allocation(LDA)

This algorithm is the most popular for topic modeling. It uses probabilistic graphical models for implementing topic modeling. We need to import the gensim package in Python for using the LDA algorithm.

Latent Semantic Analysis(LDA) or **Latent Semantic Indexing(LSI)**

The algorithm is based upon Linear Algebra. Basically, it uses the concept of SVD (Singular Value Decomposition) on the document term matrix.

Non-Negative Matrix Factorization (NMF) is also based on Linear Algebra.

All of the above-mentioned algorithms for topic modeling would have the **number of topics** as a parameter, **Document-Word Matrix** as input, and **WTM(Word Topic Matrix)** & **TDM(Topic Document Matrix)** as output.

11 Analyzing Time Series Data

Predicting the next in a given input sequence is another important concept in machine learning. This chapter gives you a detailed explanation of analyzing time series data.

11.1 Introduction

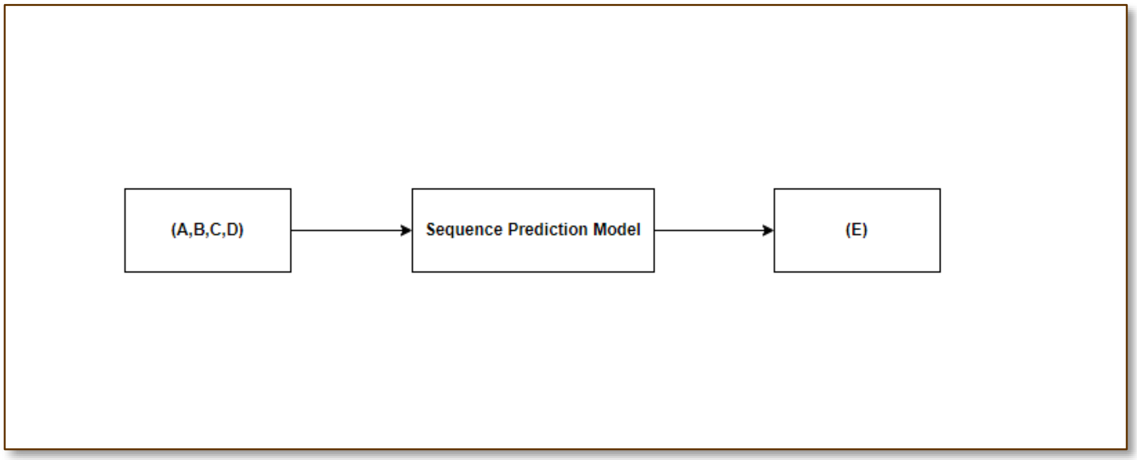
Time series data means the data that is in a series of particular time intervals. If we want to build sequence prediction in machine learning, then we have to deal with sequential data and time. Series data is an abstract of sequential data. Ordering of data is an important feature of sequential data.

Basic Concept of Sequence Analysis of Time Series Analysis

Sequence analysis or time series analysis to predict the next in a given input sequence based on the previously observed. The prediction can be of anything that may come next a symbol, a number, the next day's weather, the next term in speech, etc. Sequence analysis can be very handy in applications such as stock market analysis, weather forecasting, and product recommendations.

Example

Consider the following example to understand sequence prediction. Here **A**, **B**, **C**, and **D** are the given values and you have to predict the value **E** using a Sequence Prediction Model.



Sequence Analysis

11.2 Installing Useful Packages

For time series data analysis using Python, we need to install the following packages:

Pandas

Pandas is an open-source *BSD-licensed library* that provides high performance, ease of data structure usage, and data analysis tools for Python. You can install Pandas with the help of the following command:

```
pip install pandas
```

If you are using Anaconda and want to install by using the **conda** package manager, then you can use the following command:

```
conda install -c anaconda pandas
```

11.3 hmmlearn

It is an open source *BSD-licensed library* which consists of simple algorithms and models to learn *Hidden Markov Models(HMM)* in Python. You can install it with the help of the following command:

```
pip install hmmlearn
```

If you are using Anaconda and want to install by using the **conda** package manager, then you can use the following command:

```
conda install -c omnia hmmlearn
```

PyStruct

It is a structured learning and prediction library. Learning algorithms implemented in PyStruct have names such as *conditional random fields(CRF), Maximum-Margin Markov Random Networks (M3N)*, or *structural support vector machines*. You can install it with the help of the following command:

```
pip install pystruct
```

CVXOPT

It is used for convex optimization based on Python programming language. It is also a free software package. You can install it with the help of the following command:

```
conda install -c anaconda cvdoxt
```

11.4 Pandas: Handling, Slicing, and Extracting Statistic from Time Series Data

Pandas is a very useful tool if you have to work with time series data. With the help of Pandas, you can perform the following:

- Create a range of dates by using the **pd.date_range** package
- Index pandas with dates by using the **pd.Series** package
- Perform re-sampling by using the **ts.resample** package
- Change the frequency

Example

The following example shows you handling and slicing the time series data by using Pandas. Note that here we are using the *Monthly Arctic Oscillation data*, which can be downloaded from monthly.ao.inde.b50.current.ascii and can be converted to text format for our use.

Handling time series data

For handling time series data, you will have to perform the following steps:

The first step involves importing the following packages:

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

Next, define a function which will read the data from the input file, as shown in the code given below:

```
def read_data(input_file):
    input_data = np.loadtxt(input_file, delimiter = None)
```

Now, convert this data to time series. For this, create the range of dates of our time series. In this example, we keep one month as the frequency of data. Our file is having the data which starts from January 1950.

```
dates = pd.date_range('1950-1', periods = input_data.shape[0], freq = 'M')
```

In this step, we create the time series data with the help of Pandas Series, as shown below:

```
output - pd.Series(input_data[:, index], index = dates)
return output

if __name ==' __main__':
```

Enter the path of the input file as shown here:

```
input_file = "/Users/admin/Ai.txt"
```

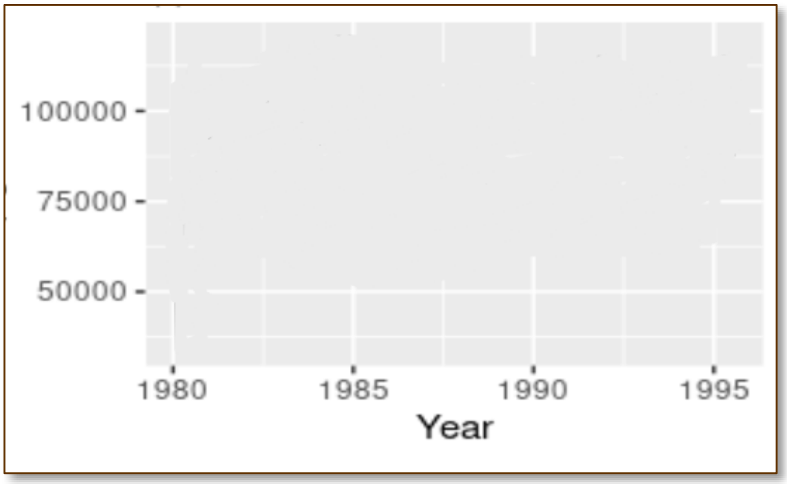
Now, convert the column to time-series format, as shown here:

```
timeseries = read_data(input_file)
```

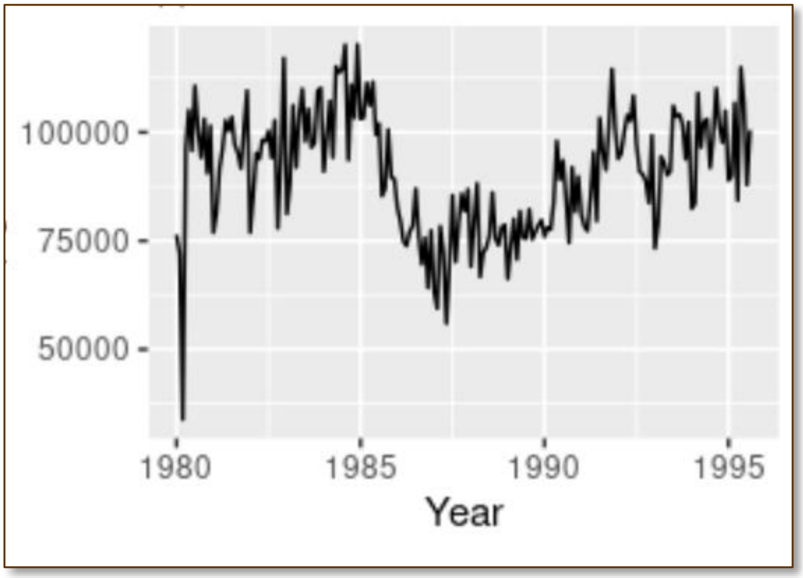
Finally, plot and visualize the data, using the commands shown:

```
plt.figure()
timeseries.plot()
plt.show()
```

You will observe the plots as shown in the following images:



Plot



Output

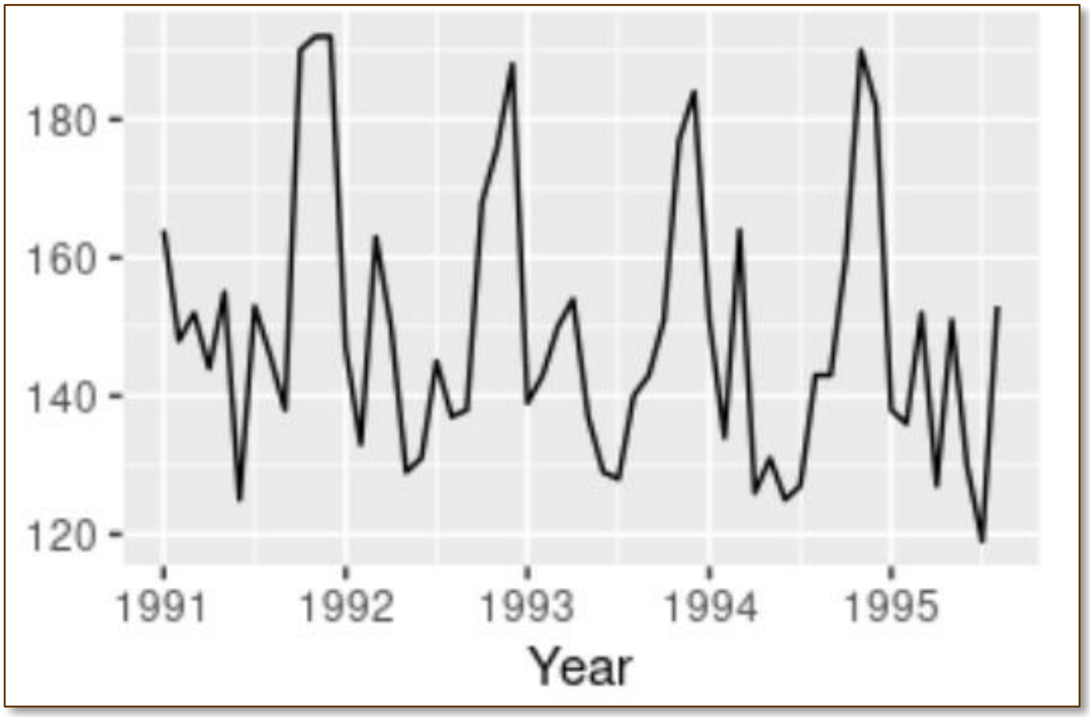
Slicing time series data

Slicing involves retrieving only some part of the time series data. As a part of the example, we are slicing the data only from 1980 to 1990. Observe the following code that performs this task

```
timeseries['1890':'1990'].plot()
  <matplotlib.axes_subplots.AxesSubplot at 0xa0e4b00>

plt.show()
```

When you run the code for slicing the time series data, you can observe the following graph as shown in the image here:



Output

11.5 Extracting Statistics from Time Series Data

You will have to extract some statistics from a given data, in cases where you need to draw some important conclusion. Mean, variance, correlation, maximum value, and the minimum value are some of such statistics. You can use the following code if you want to extract such statistics from a given time series data:

Mean

You can use the **mean()** function, for finding the mean as shown here:

```
timeseries.mean()
```

Then the output that you observe for the example discussed is:

```
-0.11143128162387
```

Maximum

You can use the **max()** function, for finding the maximum as shown here:

```
timeseries.max()
```

Then the output that you will observe for the example discussed is:

```
3.4952999999999999
```

Minimum

You can use the **min()** function, for finding the minimum, as shown here:

```
timeseries.min()
```

Then the output that you will observe for example discussed is:

```
-4.2656999999999999
```

Getting everything at once

If you want to calculate all statistics at a time, you can use the **describe()** function as shown here:

```
timeseries.describe()
```

Then the output that you will observe for the example discussed is:

```
count    817.00000
mean     -0.111431
std       1.003151
min      -4.265700
25%      -0.649430
50%      -0.042744
75%       0.475720
max       3.495300
dtype:   float64
```

Re-sampling

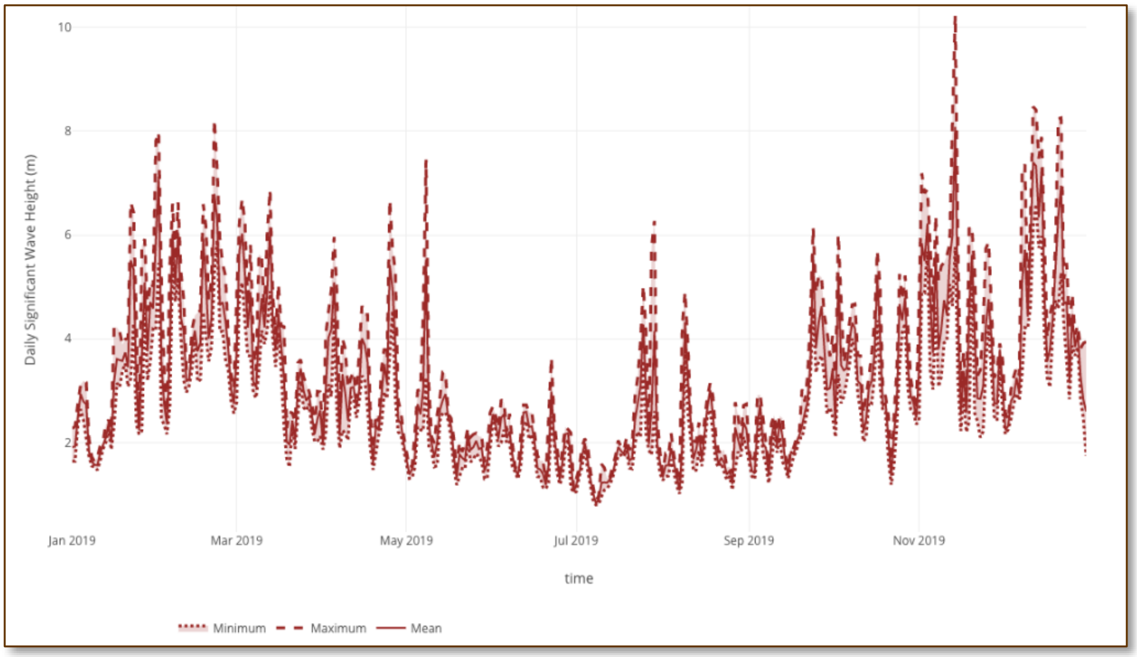
You can resample the data to a different time-frequency. The two parameters for performing re-sampling are

- Time period
- Method

Re-sampling with a mean()

You can use the following code to resample the data with the mean() method, which is the default method:

```
timeseries_mm = timeseries.resample("A").mean()
timeseries_mm.plot(style = 'g--')
plt.show()
```



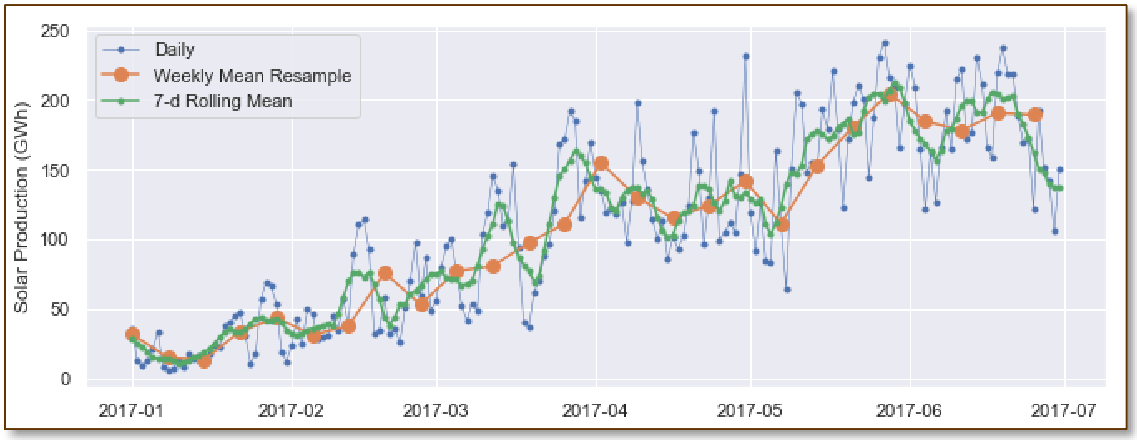
Re-sampling with a mean()

Re-sampling with median()

You can use the following code to resample the data using the **median()** method:

```
timseries_mm = timseries.resample("A").median()
timeserries_mm.plot()
plot.show()
```

Then, you can observe the following graph as the output of re-sampling with a **mean()**:



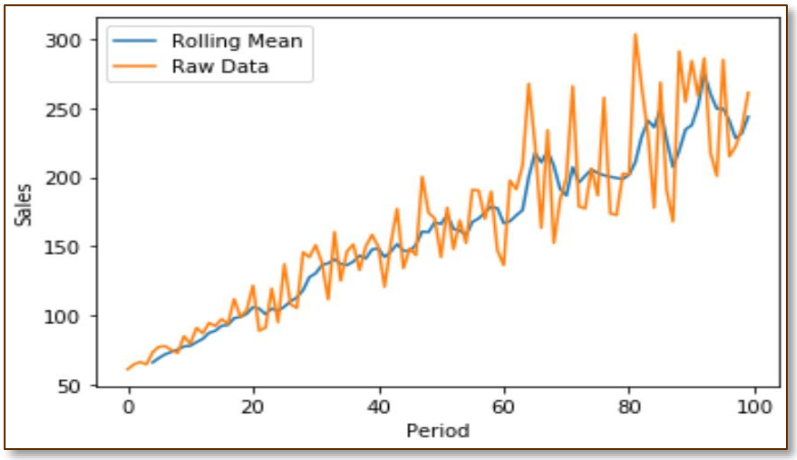
Re-sampling with median()

Rolling Mean

You can use the following code to calculate the **rolling (moving) mean**:

```
timeseries.rolling(windows = 12, center = False).mean().plot(style =
'g')
plt.show()
```

Then, you can observe the following graph as the output of the rolling (moving) mean:



Rolling mean

11.6Analyzing Sequential Data by Hidden Markov Model (HMM)

HMM is a statistical model which is widely used for data having continuation and extensibility such as time series stock market analysis, health checkup, and speech recognition. This section deals in detail with analyzing sequential data using *Hidden Markov Model (HMM).*

Hidden Markov Model (HMM)

HMM is a stochastic model which is built upon the concept of the Markov chain based on the assumption that the probability of future stats depends only on the current process state rather any state that preceded it. For example, when tossing a coin, we cannot say that the result of the fifth toss will be a head. This is because a coin does not have any memory and the next result does not depend on the previous result.

Mathematically, HMM consists of the following variables:

States (S) It is a set of hidden or latent states present in an HMM. It is denoted by **S**.

Output Symbols (O) It is a set of possible output symbols present in an HMM. It is denoted by **0**.

State Transition Probability Matrix (A) It is the probability of making a transition from one state to each of the other states. It is denoted by **A**.

Observation Emission Probability Matrix (B) It is the probability of emitting/observing a symbol at a particular state. It is denoted **B**.

Prior Probability Matrix (Pi) It is the probability of starting at a particular state from various states of the system. It is denoted by **Pi**.

Hence, an HMM may be defined as **sigma = (S, O, A, B, pi)**, where,

- **S = {s1, s2, … Sn}** is a set of **N** possible states,
- **O = {o1, o2, … om}** is a set of **M** possible observation symbols,
- **A** is an NxN state Transition Probability Matrix (TPM),
- **B** is an *NxM observation or Emission Probability Matrix (EPM)*,
- **pi** is an *N-dimensional initial state probability distribution vector*.

11.7 Example: Analysis of Stock Market data

In this example, we are going to analyze the data of the stock market, step by step, to get an idea about how the HMM works with sequential or time series data. Please note that we are implementing the example in Python.

Import the necessary package as shown below:

```
import datetime
import warnings
```

Now, use the stock market data from the **matpotlib.finance** package, as shown here:

```
import numpy as np
from matplotlb import cm, pyplot as plt
from matplotlib.dates import YearLocator, MonthLocator
try:
    from matplotlib.finance import quotes_historical_yahoo_och1
except ImportError:
    from matplotlib.finance import (
      quotes_historical_yahoo as quotes_historical_yahoo_och1)
from hmmlearn.hmm import GaussianHMM
```

Load the data from a *start date and end date*, i.e., between two specific dates as shown here:

```
start_date = datetime.date(1995, 10, 10)
end_fate = datetime.date(2015, 4, 25)
quotes = quotes_historical_yahoo_och1('INTC', start_date, end_date)
```

In this step, we will extract the closing quotes every day. For this, use the following command:

```
volumes = np.array([quote[5] for quote in quotes])[1:]
```

Here, take the percentage difference of closing stock prices, using the codes shown below:

```
diff_percentages = 100.0 * np.diff(closing_quotes) / closing_quotes[:-]
dates = np.array([quote[0] for quote in quotes], dtype = np.int)[1:]
training_data = np.column_stack([diff_percentages,volumes])
```

In this step, create and train the Gaussian HMM. For this, use the following code:

```
hmm = GaussianHMM(n_components = 7, covariance_type = 'diag', n_iter = 
1000)
with warnings.catch_warnings():
    warnings.simplefilter('ignore')
    hmm.fit(training_data)
```

Now, generate data using the HMM model, using the commands shown:

```
plt.figure()
plt.title('Difference percentages')
plt.plot(np.arrange(num_samples), samples [:,0, c='black'])
```

Use the following code to plot and visualize the volume of shares trades:

```
plt.figure()
plt.title('Volume of shares')
plt.plot(np.arrange(num_samples), samples[:, 1], c = 'black')
```

Use the following code to plot and visualize the volume of shares traded:

```
plt.figure()
plt.title('Volume of shartes')
plt.plot(np.arrange(num_samples), samples[:,1], c = 'blacl')
plt.ylim(ymin = 0)
plt.show()
```

12 Speech Recognition

In this chapter, we will learn about speech recognition using AI with Python.

Speech is the most basic means of adult human communication. The basic goal of speech processing is to provide an interaction between a human and a machine.

Speech processing system has mainly three tasks:

- **First**, speech recognition that allows the machine to cats the words, phrases, and sentences we speak
- **Second**, natural language processing to allows the machine to understand what we speak, and
- **Third**, speech synthesis to allow the machine to speak.

This chapter focuses on **speech recognition**, the process of understanding the words that are spoken by human beings. Remember that the speech signals are captured with the help of a microphone and then it has to be understood by the system.

12.1 Building a Speech Recognizer

Speech Recognition or *Automatic Speech Recognition (ASR*) is the center of attention for AI projects like robotics. Without *ASR*, it is not possible to imagine a cognitive robot interacting with a human. However, it is not quite easy to build a speech recognizer.

Difficulties in developing a speech recognition system

Developing a high-quality speech recognition system is really a difficult problem. The difficulty of speech recognition technology can be broadly characterized along a number of dimensions as discussed below:

- **Size of the vocabulary**: Size of the vocabulary impacts the ease of developing an ASR. Consider the following sizes of vocabulary for a better understanding.

  A **small size** vocabulary consists of *2-100* words, for example, as in a voice-menu system

  A **medium size** vocabulary consists of several *100s* to *1000s* of words, for example, as in a database-retrieval task

  A **large size** vocabulary consists of several *10000s* of words, as in a general dictation task.

Note that, the larger the size of the vocabulary, the harder it is to perform recognition.

- **Channel characteristics**: Channel quality is also an important dimension. For example, human speech contains high bandwidth with a full frequency range, while telephone speech consists of low bandwidth with a limited frequency range. Note that it is harder in the latter.
- **Speaking mode**: The ease of developing an *ASR* also depends on the speaking mode, that is whether the speech is in isolated word mode, connected word mode, or in continuous speech mode. Note that continuous speech is harder to recognize.
- **Speaking style**: A read speech may be in a formal style, or spontaneous and conversational with a casual style. The latter is harder to recognize.
- **Speaker dependency**: Speech can be *speaker-dependent, speaker-adaptive,* or *speaker independent*. A speaker's independence is the hardest to build.
- **Type of noise**: Noise is another factor to consider while developing an *ASR*. Signal-to-noise ratio may be in various ranges, depending on the acoustic environment that observes less versus more background noise:

    If the signal-to-noise ratio is greater than *30dB*, it is considered a a **high range**

    If the signal-to-noise ratio lies between *30dB* to *10db*, it is considered as **medium SNR**

    If the signal to noise ratio is lesser than *10dB*, it is considered as **low range**

For example, the type of background noise such as stationary, non-human noise, background speech and crosstalk by other speakers also contributes to the difficulty of the problem.

- **Microphone characteristics**: The quality of the microphone may be good, average, or below average. Also, the distance between the mouth and the microphone can vary. These factors also should be considered for recognition systems.

Despite these difficulties, researchers worked a lot on various aspects of speech such as understanding the *speech signal,* and *the speaker,* and *identifying the accents*.

You will have to follow the steps given below to build a speech recognizer.

12.2 Visualizing Audio Signals - Reading from a File and Working on it

This is the first step in building a speech recognition system as it gives an understanding of how an audio signal is structured. Some common steps that can be followed to work with audio signals are as follows:

Recording

When you have to read the audio signal from a file, then record it using a microphone, at first.

Sampling

When recording with a microphone, the signals are stored in a digitized form. But to work on it, the machine needs them in the discrete numeric form. Hence, we should perform sampling at a certain frequency and convert the signal into a discrete numerical form. Choosing the high frequency for sampling implies that when humans listen to the signal, they feel it as a continuous audio signal.

Example

The following example shows a stepwise approach to analyzing an audio signal, using Python, which is stored in a file. The frequency of this audio signal is *44,100 HZ*.

Import the necessary packages as shown here:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.io import wavfile
```

Now, read the stored audio file. It will return two values: the sampling frequency and the audio signal. Provide the path of the audio file where it is stored, as shown here:

```
frequency_sampling, audio_signal =
wavfile.read("/Users/admin/aduio_file.wav")
```

Display the parameters like sampling frequency of the audio signal, data type of signal and its duration, using the commands shown:

```
print('\nSignal shape:', audio_signal.shape)
print('Signal Datatype:', audio_signal.dtype)
print('Signal duration:', round(audio_signal.shape[0] /
floadt(frequency_sampling), 2), 'seconds')
```

The step involves normalizing the signal as shown below:

```
audio_signal = audio_signal / np.power(2,15)
```

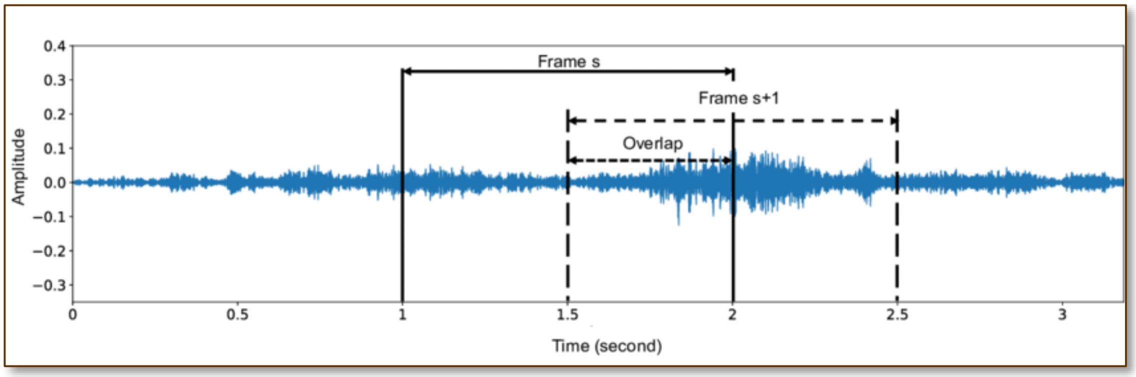
In this step, we are extracting the first 100 values from this signal to visualize. Use the following commands for this purpose:

```
audio_signal = audio_signal [:100]
time_axis = 1000 * np.arrange(0, len(signal), 1) /
float(frequency_sampling)
```

Now, visualize the signal using the commands given below:

```
plt.plot(time_axis, signal, color='blue')
plt.xlabel('Time(milliseconds)')
plt.ylabel('Amplitude')
plt.title('Input audio signal')
plt.show()
```

You would be able to see an output graph and data extracted for the above audio signal as shown in the image here:



Framing Sound

```
Signal shape: (132300,)
Signal Datatype: int16
Signal duration: 3.0 seconds
```

12.3 Characterizing the Audio Signal: Transforming to Frequency Domain

Characterizing an audio signal involves converting the time domain signal into the frequency domain, and understanding its frequency components, by. This is an important steps because it gives a lot of information about the signal. You can use a mathematical tool like Fourier Transform to perform this transformation.

Example The following example shows, step-by-step, how to characterize the signal, using Python, which is stored in a file. Note that here we are using *Fourier Transform mathematical tool* to convert it into the frequency domain.

Important the necessary packages, as shown here:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.io import wavfile
```

Now, read the stored audio file. It will return two values: the sampling frequency and the audio signal. Provide the path of the audio file where it is stored as shown in the command here:

```
frequency_sampling, audio_signal =
wavfile.read("/Users/admin/sample.wav")
```

In this step, we will display the parameters like sampling frequency of the audio signal, the data type of signal, and its duration, using the command given below:

```
print('\nSignal shape:', audio_signal.shape)
print('Signal Datatype:', audio_signal.dtype)
print('Signal duration:', round(audio_signal.shape[0] /
float(frequency_sampling), 2), 'seconds')
```

In this step, we need to normalize the signal, as shown in the following command:

```
audio_signal = audio_signal / np.power(2, 15)
```

This step involves extracting the length and half length of the signal. Use the following commands for this purpose:

```
length_signal = len(audio_signal)
half_length = np.ceil((length_signal +1) / 2.0).astype(np.int)
```

Now, we need to apply mathematical tools for transforming into the frequency domain. Here we are using the Fourier Transform.

```
signal_frequency = np.fft.fft(audio_signal)
```

Now, do the normalization of frequency domain signal and square it:

```
signal_frequency = abs(signal_frequency[0:half_length]) / length_signal
signal_frequency = **=2
```

Next, extract the length and half length of the frequency transformed signal:

```
len_fts = len(signal_frequency)
```

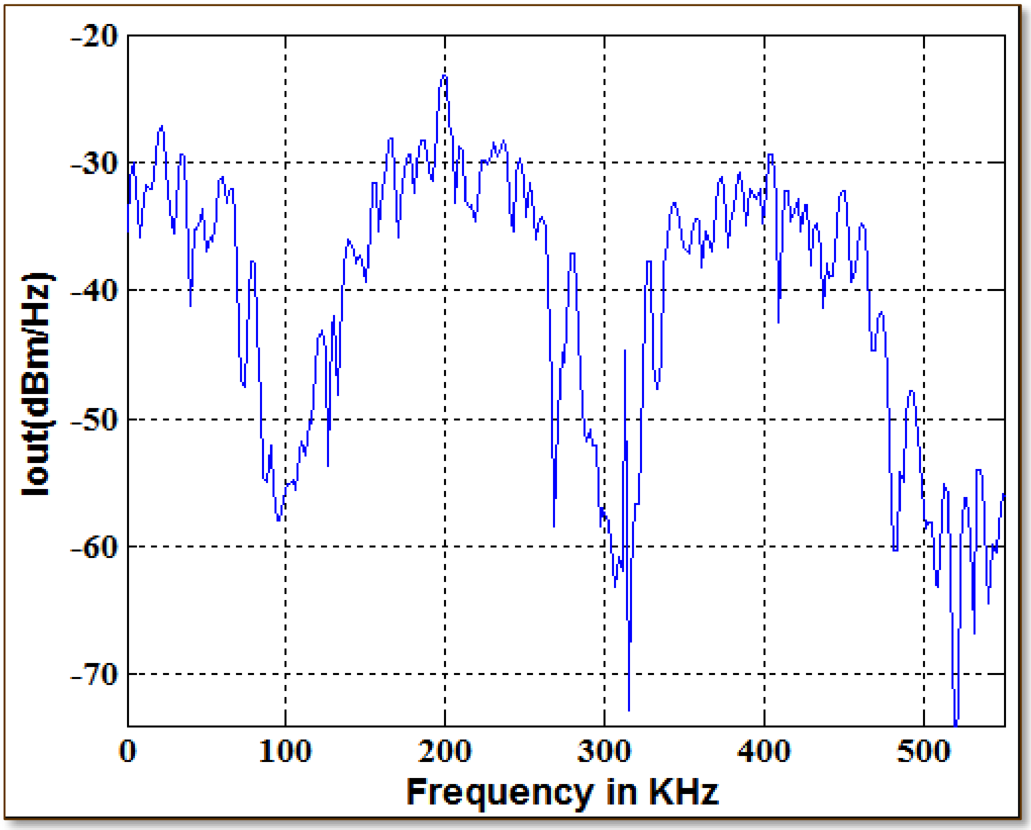
Note that the Fourier transformed signal must be adjusted for even as well as odd case.

```
if length_signal % 2
   signal_frequency[1:len_fts] *=2
else
   signal_frequency[1:len_fts-1] *= 2
```

Now visualize the characterization of the signal as follows:

```
plt.figure()
plt.plot(x_axis, signal_power, color='black')
plt.xlabel('Frequency(kHz)')
plt.ylabel('Signal power (dB)')
plt.show()
```

You can observe the output graph of the above code as shown in the image below:



Visualize the Characterization

12.4Generating Monotone Audio Signal

The two steps that you have seen till now are important to learn about signals. Now, this step will be useful if you want to generate the audio signal with some predefined parameters. Note that this step will save the audio signal in an output file.

Example

In the following example, we are going to generate a monotone signal, using Python, which will be stored in a file. For this, you will have to take the following steps:

Import the necessary packages as shown:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.io.wavfile import write
```

Provide the file where the output file should be saved

```
output_file = 'audio_signal_generated.wav'
```

Now, specify the parameters of your choice, as shown:

```
duration = 4 # in seconds
frequency_sampling = 44100 # in Hz
frequency+tone = 784
min_val = -4 * np.pi
max_val = 4 * np.pi
```

In this step, we can generate the audio signal, as shown:

```
t = np.linspace(min_val, max_val, duration * frequency_sampling)
audio_signal = np.sin(2* np.pi * tone_freq * t)
```

Now, save the audio file in the output file:

```
write(output_file, frequency_sampling, signal_scaled)
```

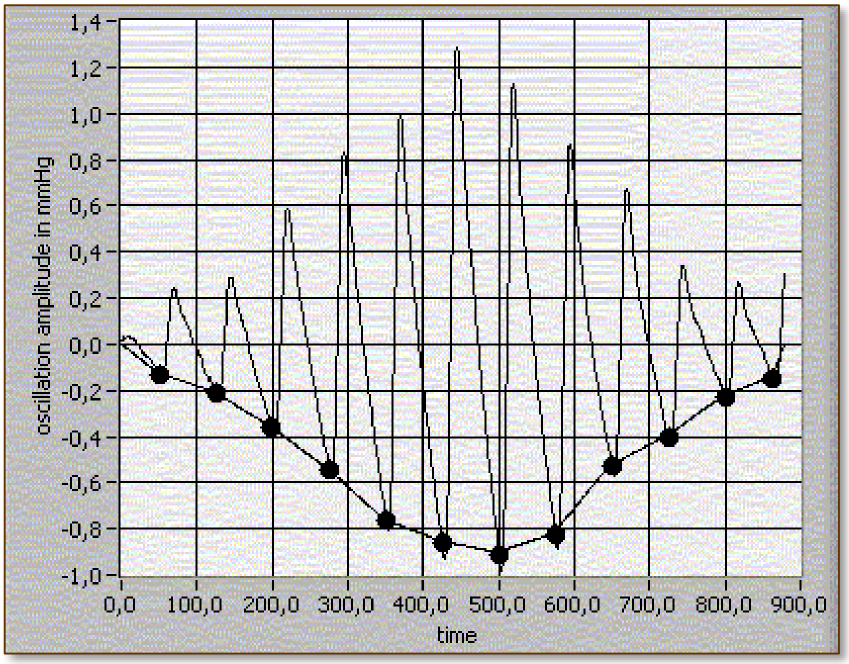
Extract the first 100 values for our graph, as shown:

```
audio_signal = audio_signal[:100]
time_axis = 1000 * np.arrange(0, len(signal), 1) / float(sampling_freq)
```

Now, visualize the generated audio signal as follows:

```
plt.plot(time_axis, signal, color='blue')
plt.xlabel('Time in milliseconds')
plt.ylabel('Amplitude')
plt.title('Generated audio signal')
plt.show()
```

You can observe the plot as shown in the figure given here:



Visualize the generated audio signal

12.5 Feature Extraction from Speech

This is the most important step in building a speech recognizer because after converting the speech signal into the frequency domain, we must convert it into the usable form of the feature vector. We can use different feature extraction techniques like *MFCC, PLP, PLP-RASTA, etc.* for this purpose.

Example

In the following example, we are going to extract the features from the signal, step-by-step, using Python, by using the *MFCC technique*.

Import the necessary packages, as shown here:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.io import wavfile
from python_speech_features import mfcc, logfbank
```

Now, read the stored audio file. It will return two values - the sampling frequency and the audio signal. Provide the path of the audio file where it is stored.

```
frequency_sampling, audio_signal =
wavfile.read("/Users/admin/audio_file.wav")
```

Note that here we are talking the first *15000* samples for analysis.

```
audio_signal = audio_signal[:15000]
```

Use the *MFCC techniques* and execute the following command to extract the *MFCC features*:

```
features_mfcc = mfcc(audio_signal, frequency_sampling)
```

Now, print the *MFCC parameters*, as shown:

```
print('\nMFCC:\nNumber of windows =', features_mfcc.shape[0])
print('Length of each feature=', features_mfcc.shape[1])
```

Now, plot and visualize the *MFCC features* using the commands given below:

```
features_mfcc = features_mfcc.T
plt.matshow(features_mfcc)
plt.titile('MFCC')
```

In this step, we work with the filter bank features as shown:

Extract the filter bank features:

```
filterbank_features = logfbank(audio_signal, frequency_sampling)
```

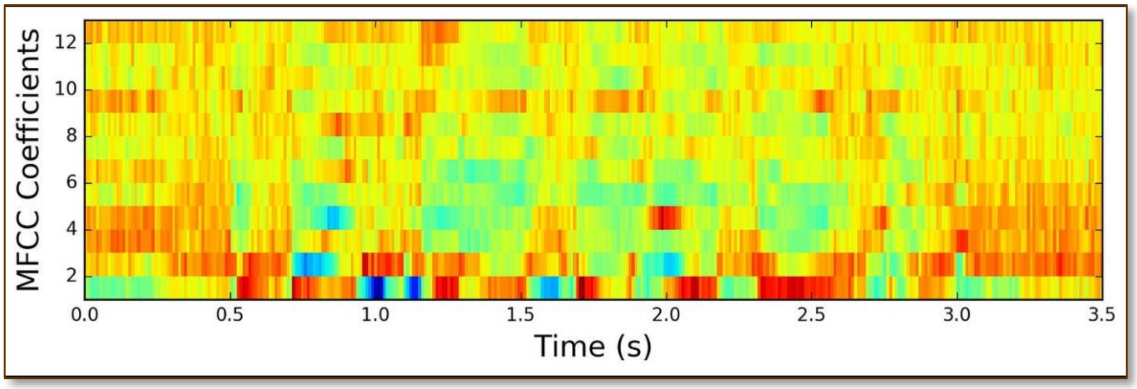
Now, print the filterbank parameters.

```
print('\nFilter bank:\nNumber of windows =',
filterbank_features.shape[0])
print('Length of each feature =', filterbank_features.shape[1])
```

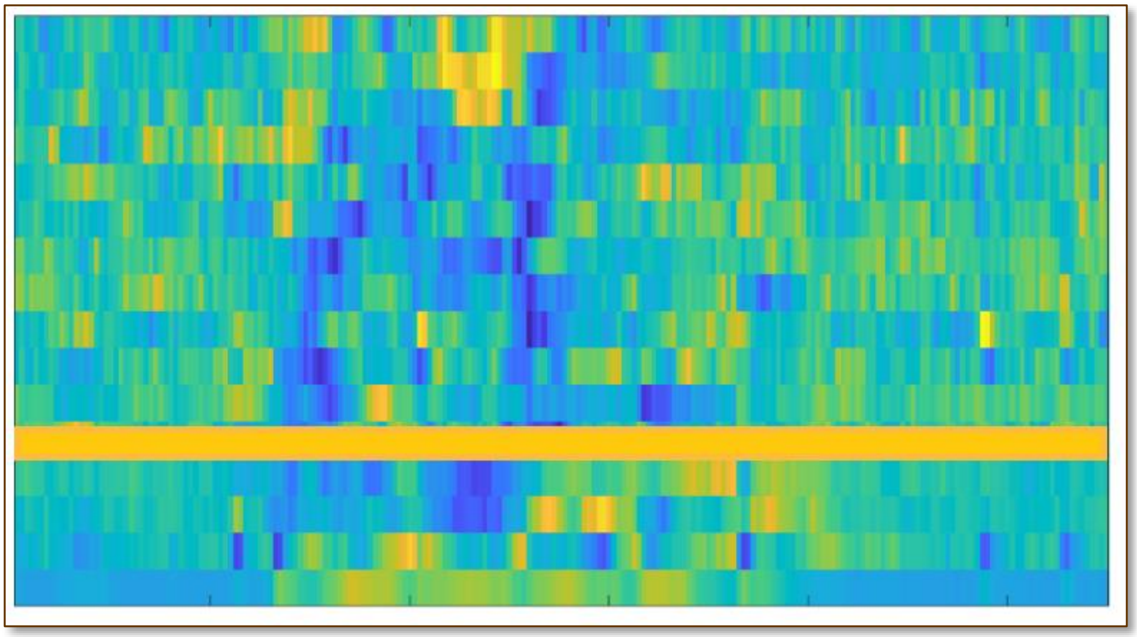
Now, plot and visualize the filterbank features.

```
filterbank_features = filterbank+features.T
plt.matshow(filterbank_features)
plt.title('Filter bank')
plt.show()
```

As a result of the steps above, you can observe the following output: *Figure 1 for MFCC* and *Figure 2 for Filter Bank*.



MFCC



Filter Bank

12.6 Recognition of Spoken Words

Speech recognition means that when humans are speaking, a machine understands it. Here we are using *Google Speech API* in Python to make it happen. We need to install the following packages for this:

- **Pyaduio**: It can be installed by using the **pip install Pyaudio** command.
- **SpeechRecognition**: This package can be installed by using **pip install SpeechRecognition**.
- **Google-Speech-API**: It can be installed by using the command **pip install google-api-python-client**.

Example

Observer the following example to understand about recognition of spoken words:

Import the necessary packages as shown:

```
import speech_recognition as sr
```

Create an object as shown below:

```
recording = sr.Recognizer()
```

Now, the **Microphone()** module will take the voice as input:

```
with sr.Microphone() as source:
recording.adjust_for_ambient_noise(source)
    print("Please Say something:")
    audio = recording.listen(source)
```

Now *Google API* would recognize the voice and gives the output:

```
try:
    print("You said: \n" + recording.recognize_google(audio))
except Exception as e:
    print(e)
```

You can see the following output:

```
Please Say Something:
You said:
```

For **example**, if you said **tutorialspoint.com**, then the system recognizes it correctly as follows:

```
turorialspoint.com
```

13 Heuristic Search

Plays a key role in artificial intelligence. In this chapter, you will learn in detail about it.

13.1 Concept of Heuristic Seach in AI

Heuristic is a rule of thumb that leads us to the probable solution. Most problems in artificial intelligence are of exponential nature and have many possible solutions. You do not know exactly which solutions are correct and checking all the solutions would be very expensive.

Thus, the use of heuristics narrows down the search for a solution and eliminates the wrong options the method of using heuristics to lead the search in search space is called heuristic Search. Heuristic techniques are very useful because the search can be boosted when you use them.

13.2 Difference between Uniformed and Informed Search

There are two types of control strategies or search techniques uninformed and informed. They are explained in detail as given here:

Uninformed Search

It is also called blind search or blind control strategy. It is named so because there as information only about the problem definition, and no other extra information is available about the states. This kind of search technique would search the whole state space for getting the solution. *Breadth First Search (BFS)* and *Depth First Search (DFS)* are examples of uninformed searches.

Informed Search

It is also called heuristic search or heuristic control strategy. It is named so because there is some extra information about states. This extra information is useful to complete the preference among the child nodes to explore and expand. There would be a heuristic function associated with each node. *Best First Search (BFS), A*, Mean,* and *Analysis* are examples of informed searches.

Constraint Satisfaction Problems (CSPs)

Constraint means restriction or limitation. In AI, constraint satisfaction problems are problems that must be solved under some constraints. The focus must be on not violating the constraint while solving such problems. Finally, when we reach the final solution, CSP must obey restrictions.

13.3 Real-World Problem Solved by Constraint Satisfaction

The previous selection dealt with creating constraint satisfaction problems. Now, let us apply this to real-world problems too. Some examples of real-world problems solved by constraint satisfaction are as follows:

Solving algebraic relation

With the help of constraint satisfaction problem, we can solve algebraic relations. In this example, we will try to solve a simple algebraic relation **a*2 = b.** It will return the value of **a** and **b** within the range that we would define.

After completing this Python program, you would be able to understand the basics of solving problems with constraint satisfaction.

Note that before writing the program, we install a Python package called python-constraint. You can install it with the help of the following command:

```
pip install python-constraint
```

The following steps show you a Python program for solving algebraic relations using constraint satisfaction:

Import the **constraint** package using the following command:

```
from constraint import *
```

Now, create an object of a module named **problem()** as shown below:

```
problem = Problem()
```

Now, define variables. Note that here we have two variables **a** and **b**, and we are defining **10** as their range, which means we got the solution within the first **10** numbers.

```
problem.addVariable('a', range(10))
problem.addVariable('b', range(10))
```

Next, define the particular constraint that we want to apply to this problem. Observe that here we are using the constraint **a*2 = b**

```
problem.addConstraint(lambda a, b: a * 2 == b)
```

Now, create the object of **getSolution()** module using the following command:

```
solutions = problem.getSolution()
```

Lastly, print the output using the following command:

```
print (solutions)
```

You can observe the output of the above program as follows:

```
[{'a':4, 'b':8}, {'a':3,'b':6}, {'a':2, 'b':4},{'a':1,'b':2},{'a':0,'b':0}]
```

Magic Square

A magic square is an arrangement of distinct numbers, generally integers, in a square grid, where the numbers in each room and in each column, and the numbers in the diagonal, all add up to the same number called the *magic constant*.

The following is a stepwise execution of simple Python code for generating magic squares:

Define a function named **magic_square**, as shown below:

```
def magic_square(matrix_ms):
    iSize = len(matrix_ms[0])
    sum_list = []
```

The following code shows the code for vertical of squares:

```
for col in range(iSize):
    sum_list.append(sum(row[col] for row in matrix_ms))
```

The following code shows the code for horizontal of squares:

```
sum_list.extend([sum (lines) for lines in matrix_ms])
```

The following code shows the code for horizontal of squares:

```
dlResult = 0
for i in range(o,iSize):
    dlResult +=matrix_ms[i][i]
sum_list.append(dlResult)
drResult = 0
for i in range(iSize-1, -1, -1):
    drResult +=matrix_ms[i][i]
sum_list.append(drResult)

if len(set(sum_list))>1:
    return False
return True
```

Now give the values of the matrix and check the output

```
print(magic_square([[1,2,3],[4,5,6], [7,8,9]]))
```

You can observe that the output would be **False** as the sum is not up to the same number.

```
print(magic_square([[3,9,2], [3,5,7], [9,1,6]]))
```

You can observe that the output would be **True** as the sum is the same number, that is **15** here.

14 Gaming

Games are played with strategy. Every player or team would make a strategy before starting the game and they have to change or build new strategies according to the current situation(s) in the game.

14.1 Search Algorithms

You will have to consider computer games also with the same strategy as above. Note that Search Algorithms are the ones that figure out the strategy in computer games.

How it works

The goal of search algorithms is to find the optimal set of moves so that they can reach the final destination and win. These algorithms use the winning set of conditions, different for every game, to find the best moves.

Visualize a computer game as a tree. We know that tree has noes. Starting from the root, we can come to the final winning node, but with optimal moves. That is the work of search algorithms. Every node in such a tree represents a future state. The search algorithms search through this tree to make decisions at each step or node of the game.

14.2 Combination Search

The major disadvantage of using search algorithms is that they are exhaustive in nature, which is why they explore the entire search space to find the solution that leads to a waste of resources. It would be more cumbersome if these algorithms need to search the whole search space for finding the final solution.

To eliminate such kind of problem, we can use combinational search which uses the heuristic to explore the search space and reduces its size by eliminating the possible wrong moves. Hence, such algorithms can save resources. Some of the algorithms that use heuristics to search the space and save resources are discussed here:

14.3 Minimax Algorithm

It is the strategy used by a combinational search that uses heuristics to speed up the search strategy. The concept of the Minimax strategy can be understood with the example of two-player games, in which each player tries to predict the next move of the opponent and tries to minimize that function. Also, in order to win, the player always tries to maximize their own function based on the current situation.

14.4 Alpha-Beta Pruning

A major issue with the Minimax algorithm is that it can explore those parts of the tree that are irrelevant, leading to the wastage of resources. Hence there must be a strategy to decide which part of the tree is relevant and which is irrelevant and leave the irrelevant part unexplored. Alpha-Beta pruning is one such kind of strategy.

The main goal of the Alpha-Beta pruning algorithm is to avoid searching those parts of the tree that do not have any solution. The main concept of Alpha-Beta pruning is to use two bounds named **Alpha**, the maximum lower bound, and **Beta**, the minimum upper bound. These two parameters are the values that restrict the set of possible solutions. it compares the value of the current node with the value of alpha and beta parameters so that it can move the part of the tree that has the solution and discard the rest.

14.5 Negamax Algorithm

This algorithm is not different from the Minimax algorithm, but it has a more elegant implementation. The main disadvantage of using the Minimax algorithm is that we need to define two different heuristic functions. The connection between this heuristic is that the better a state of a game is for one player, the worse it is for the other player, In the Negamax algorithm, the same work of two heuristic functions is done with the help of a single heuristic function.

14.6 Building Bots to Play Games

For building bots to play two-player games in AI, we need to install the easyAI libary. It is an artificial intelligence framework that provides all the functionality to build two-player games. You can download it with the help of the following command:

```
pip install easyAI
```

14.7 A Bot to Play Las Coin Standing

In this game, there would be a pile of coins. Each player has to take a number of coins from that pile. The goal of the game is to avoid taking the last coin in the pile. We will be using the class **LastCoinStanding** inherited from the **TwoPlayers** class of the **easyAI** libary. The following code shows the Python code for this code:

Import the required packages as shown:

```
from easyAI import TwoPlayersGame, id_solve, Human_Player, AI_Player
from easyAI.AI import TT
```

Now, inherit the class from the **TwoPlayerGame** class to handle all operations of the game:

```
class LastCoin_game(TwoPlayersGame):
    def __init__(self, players):
```

Now, define the players and the players who is going to start the game.

```
self.players = players
self.nplayer = 1
```

Now, define the number of coins in the game, here we are using **15** coins for the game.

```
self.num_coins = 15
```

Define the maximum number of coins a player can take in a move.

```
self.max_coins = 4
```

Now there are certain things to define as shown in the following code. Define possible moves.

```
def possible_moves(self):
  return [str(a) for a in range(1, self.max_coins +1)]
```

Define the removal of the coins.

```
def win_game(self):
  return self.num_coins <= 0
```

Define when to stop the game, that is when somebody wins.

```
def is_over(self):
  return self.win()
```

Define how to compute the score.

```
def score(self):
  return 100 if self.win_game() else 0
```

Define the number of coins remaining in the pile.

```
def show(self):
  print(self.num_coins, 'coins left in the pile')
if __name__ == " __main__":
    tt = TT()
    LastCoin_game.ttentry = lambda self: self.num_coins
```

Solving the game with the following code block:

```
r, d, m = id_solve(LastCoin_game,
    range(2, 20), win_score=100, tt=tt)
print(r, d, m)
```

Deciding who will start the game:

```
game = LastCoing_game([AI_Player(tt), Human_Player()])
game.play()
```

You can find the following output and a simple play of this game:

```
d:2, a:0, m:1
d:3, a:0, m:1
d:4, a:0, m:1
d:5, a:0, m:1
d:6, a:100, m:4
1  6  4
16 coins left in the pile
Move #1: player 1 plays 4:
11 coins left in the pile
Player 2 what do you play? 2
Move #2: player 2 plays 2:
9 coins left in the pile
Move #3: player 1 plays 3:
6 coins left in the pile
Player 2 what do you play? 1
Move #4: player 2 plays 1:
5 coins left in the pile
Move #5: player 1 plays 4:
1 coin left in the pile
Player 2 what do you play? 1
Move #6: player 2 plays 1 :
0 coins left in the pile
```

14.8A bot to Play Tic Tac Toe

Tic-Tac-Toe is very familiar and one of the most popular games. Let us create this game by using the **easyAI** libary in Python. The following code is the Python code of this game:

Import the packages as shown:

```
from easyAI import TwoPlayersGame, AI_Player, and Negamax
from easyAI.Player import Human_Player
```

Inherit the class from the **TwoPlayerGame** class to handle all operations of the game:

```
class TicTacToe_game(TwoPlayersGame):
  def __init__(self,players):
```

Now, define the player and the player who is going to start the game:

```
self.players = players
self.nplayer = 1
```

Define the type of board:

```
self.board = [0] * 9
```

Now there are some certain things to define as follows:

Define possible moves:

```
def possible_moves(self):
  return [x + 1 for x, y in enumerate(self.board) if y == 0]
```

Define the move of a player:

```
def make_move(self, move):
  self.boardp[int(move) -1] = self.nplayer
```

To boost AI, define when a player makes a move:

```
def umake_move(self, move):
    self.board[int(move) -1] = 0
```

Define the loose condition that an opponent has three in a line:

```
def condition_for_lose(self):
  possible_combinations = [[1,2,3],[4,5,6],[7,8,9,],
    [1,4,7],[2,5,8],[3,6,9], [1,5,9], [3,5,7]]
  return any([all([(self.board[z-1] == self.nopponent)
    for z in combination]) for combination in possible_combination])
```

Define a check for the finish of game:

```
def is_over(self):
  return(self.possible_moves() == []) or self.condition_for_lose()
```

Show the current position of the player in the game

```
def show(self):
    print('\n'+'\n'.join([['.', '0', 'X'][self.board[3*j +i]]
      for i in range (3)]))
```

Compute the scores:

```
def scoring(self)
    return -100 if self.condition_for_lose() else 0
```

Define the main method to define the algorithm and start the game:

```
if __name__ == "__main__":
    algo = Negamax(7)
    TicTacToe_game([Human_Player(), AI_Player(algo)]).play()
```

You can see the following output and a simple play of this game:

```
. . .
. . .
. . .
Player 1 what do you play? 1
Move #1: player 1 plays 1 :
0 . .
. . .
. . .
Move #2: player 2 playes 5 :
0 . .
. X .
121
. . .
Player 1 what do you play? 3
Move #3: player 1 plays 3 :
0 . 0
. X .
121
. . .
Move #4: player 2 plays 2 :
0 X 0
. X .
. . .
Player 1 what do you play? 4
Move #5: player 1 plays 4
0 X 0
0 X .
. . .
Move #6: player 2, plays 8 :
0 X 0
0 X .
. X .
```

15 Neural Networks

Are parallel computing devices that attempt to make a computer model of the brain. The main objective behind this is to develop a system to perform various computational tasks faster than traditional systems. These tasks include *Pattern Recognition and Classification*, *Approximation*, *Optimization*, and *Data Clustering*.

15.1 What is Artificial Neural Networks (ANN)

Artificial Neural network (ANN) is an efficient computing system whose central theme is borrowed from the analogy of biological neural networks. ANNs are also named Artificial Neural Systems, Parallel Distributed Processing Systems, and Connectionist Systems. ANN acquires a large collection of units that are interconnected in some pattern to allow communications between them. These units also referred to as nodes or neurons, are simple processors which operate in parallel.

Every neuron is connected with another neuron through a **connection link**. Each connection link is associated with a weight having information about the input signal. This is the most useful information for neurons to solve a particular problem because the **weight** usually excites or inhibits the signal that is being communicated. Each neuron is having its internal state which is called an **activation signal**. Output signals, which are produced after combining input signals and activation rules, may be sent to other units.

If you want to study neural networks in detail then you can follow the link - Artificial Neural Network.

15.2 Installing Useful Packages

For creating neural networks in Python, we can use a powerful package for neural networks called **NeuroLab**. It is a libary of basic neural network algorithms with flexible network configuration and learning algorithms for Python. You can install this package with the help of the following command on the command prompt:

```
pip install NeuroLab
```

If you are using the Anaconda environment, then use the following command to install NeuroLab:

```
conda install -c labfabulous neurolab
```

15.3 Building Neural Networks

In this section, let us build some neural networks in Python by using the NeuroLab package.

Perception-based Classifier

Perceptions are the building blocks of ANN. If you want to know more about Perceptron, you can follow the link - *artificial_neural_network*

Following is a stepwise execution of the Python code for building a simple neural network perception-based classifier:

Import the necessary packages as shown:

```
import matplotlib.pyplot as plt
import neurolab as nl
```

Enter the input values, Note that is is an example of supervised learning, hence you will have to provide target values too.

```
input = [[0, 0], [0, 1], [1, 0], [1, 1]]
target = [[0], [0], [0], [1]]
```

Create the network with 2 inputs and 1 neuron:

```
net = nl.net.newp([[0, 1],[0, 1]], 1)
```

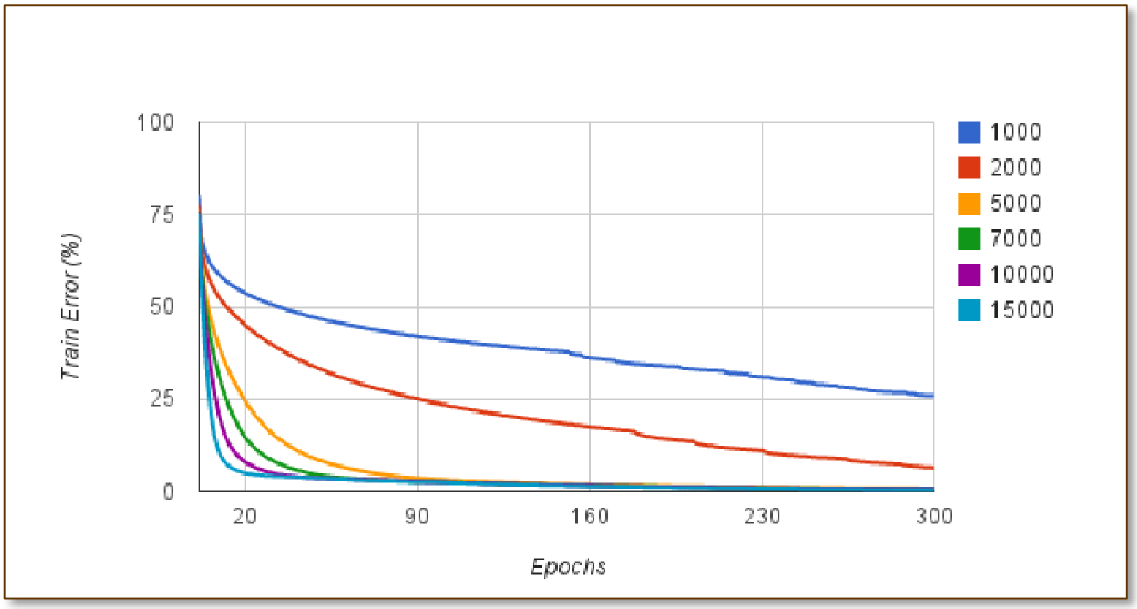
Now, train the network. Here, we are using the *Delta rule* for training.

```
error_progress = net.train(input, target, epochs=100, show=10, lr=1.1)
```

Now, visualize the output and plot the graph:

```
plt.figure()
plt.plot(error_progress)
plt.xlabel('Number of epochs')
plt.ylabel('Training error')
plt.grid()
plt.show()
```

You can see the following graph showing the training progress using the error metric:



Training Process

Single-Layer Neural Networks

In this example, we are creating a single-layer neural network that consists of independent neurons acting on input data to produce the output. Note that we are using the text file named **neural_simple.txt** as our input.

Import the useful packages as shown:

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

Load the dataset as follows:

```
input_data = np.loadtxt("/Users/admin/neural_simple.txt")
```

The following is the data we are going to use. Note that in this data, the first two columns are the features and the last two columns are the labels.

```
array([[2. , 4. , 0.  , 0.],
       [1.5, 3.9, 0.  , 0.],
       [2.2, 4.1, 0.  , 0.],
       [1.9, 4,7, 0.  , 0.],
       [5.4, 2.2, 0.  , 1.],
       [4.3, 7.1, 0.  , 1.],
       [5.8, 4.9, 0.  , 1.],
       [6.5, 3.2, 0.  , 1.],
       [3. , 2. , 1.  , 0.],
       [2.5, 0.5, 1.  , 0.],
       [3.5, 2.1, 1.  , 0.],
       [2.9, 0.3, 1.  , 0.],
       [6.5, 8.3, 1.  , 1.],
       [3.2, 6.2, 1.  , 1.],
       [4.9, 7.8, 1.  , 1.],
       [2.1, 4.8, 1.  , 1.]])
```

Now, separate these four columns into **2** data columns and **2** labels:

```
data = input_data[:, 0:2]
labels = input_data[:, 2]
```

Plot the input data using the following commands:

```
plt.figure()
plt.scatter(data[:,0], data[:,1])
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.title('Input data')
```

Now, define the minimum and maximum values for each dimension as shown here:

```
dim1_min, dim1_max = data[:,0].min(), data[:,0].max()
dim2_min, dim2_max = data[:,1].min(), data[:,1].max()
```

Next, define the number of neurons in the output layer as follows:

```
nn_output_layer = labels.shape[1]
```

Now, define a single-layer neural network:

```
dim1 = [dim1_min, dim1_max]
dim2 = [dim2_min, dim2_max]
neural_net = nl.net.newp([dim1, dim2], nn_output_layer)
```

Train the neural network with a number of epochs and learning rate as shown:

```
error = neural_net.train(data, labels, epochs = 200, 20, lr = 0.0)
```

Now, visualize and plot the training progress using the following commands:

```
plt.figure()
plt.plot(error)
plt.xlabel('Number of epochs')
plt.yxlabel('Training error')
plt.title('Training error progress')
plt.grid()
plt.show()
```

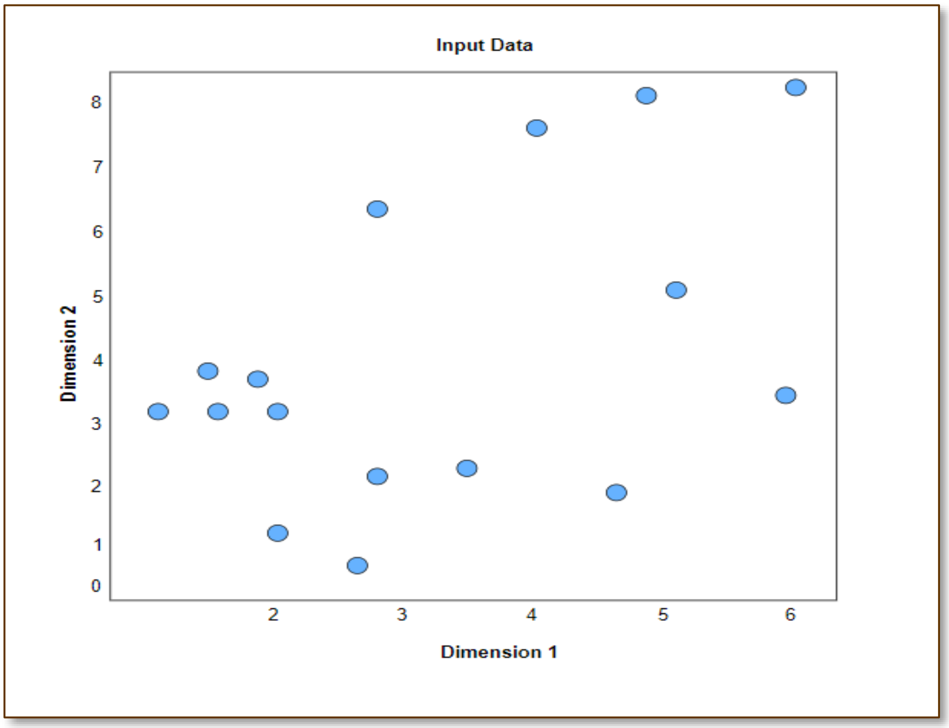
Now, use the test data points in the above classifier:

```
print('\nTest Results:')
data_test = [[1.5, 3.2], [3.6, 1.7], [3.6, 5.7], [1.6, 3.9]] for an
item in data_test:
    print(item, '-->', neural_net.sim([item])[0])
```

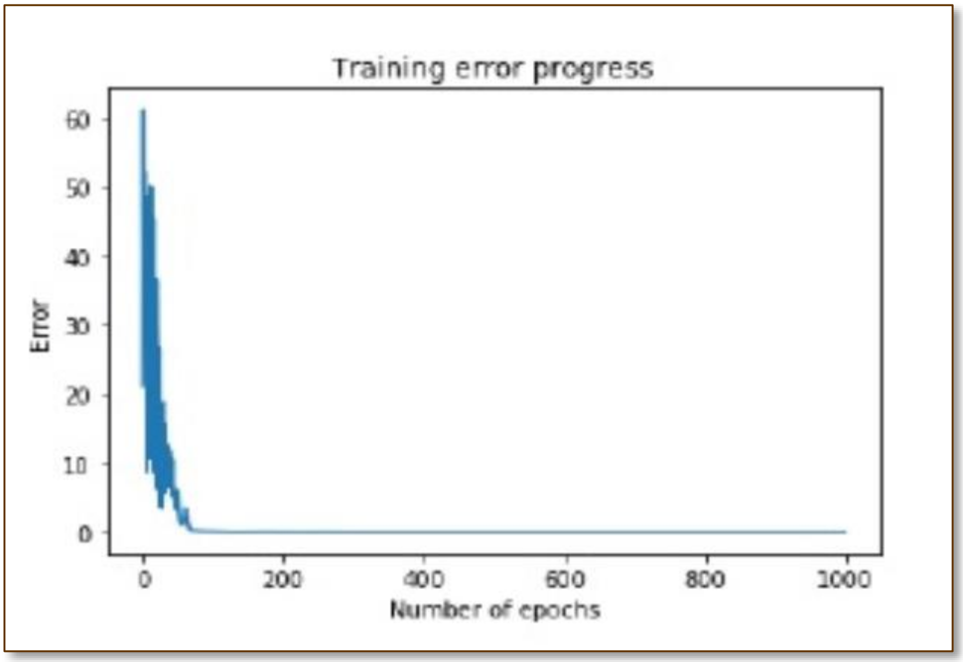
You can find the test results as shown here:

```
[1.5, 3.2] --> [1. 0.]
[3.6, 1.7] --> [1. 0.]
[3.6, 5.7] --> [1. 0.]
[1.6, 3.9] --> [1. 0.]
```

You can see the following graph as the output of the code discussed till now:



Single-Layer Neural Networks



Training Error Progress

Multi-Layer Neural Networks

In this example, we are creating a multi-layer neural network that consists of more than one layer to extract the underlying pattern in the training data. This multilayer neural network will work like a regressor. We are going to generate some data points based on the equation: **y=2x(2)+8**

Import the necessary packages as shown:

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

Generate some data points based on the above-mentioned equation:

```
min_val = -30
max_val = 30
num_points = 160
x = np.linspace(min_val, max_val, num_points)
y = 2 * np.squre(x) + 8
y /= np.linalg.norm(y)
```

Now, reshape this data set as follows:

```
data = x.reshape(num_points, 1)
labels = y.reshape(num_points, 1)
```

Visualize and plot the input data set using the following commands:

```
plt.figure()
plt.scatter(data, labels)
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.title('Data-points')
```

Now, build the neural network having two hidden layers with **neurolab** with **ten** neurons in the first hidden layer, **six** in the second hidden layer, and **one** in the output layer.

```
neural_net = nl.net.newff([[min_val, max_val]], [10, 6, 1])
```

Now use the gradient training algorithm:

```
neural_net.trainf = nl.train.train_gd
```

Now train the network with the goal of learning on the data generated above:

```
error = neural_net.train(data, labels, epochs = 1000, show = 100, hoal
= 0.01)
```

Now, run the neural networks on the training data points:

```
output = neural_net.sim(data)
x_pred = output.reshape(num_points)
```

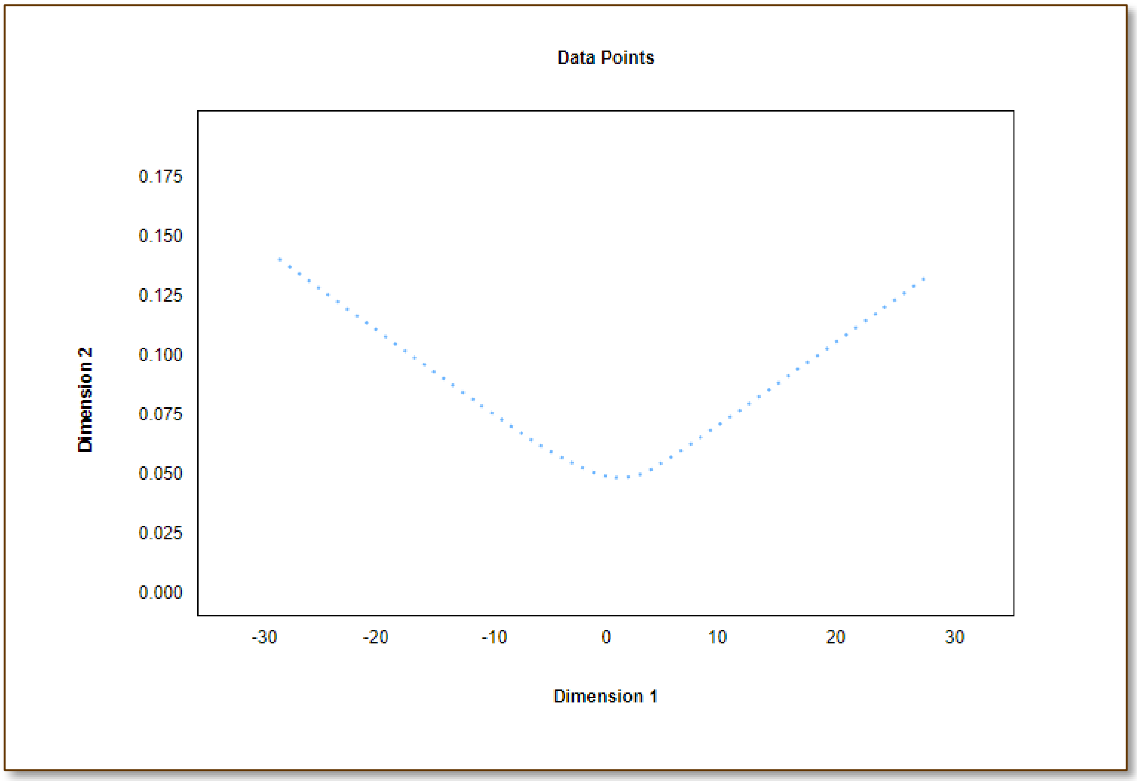
Now plot and visualize task:

```
plt.figure()
plt.plot(error)
plt.xlabel('Number of epochs')
plt.ylabel('Error')
plt.title('Training error progress')
```

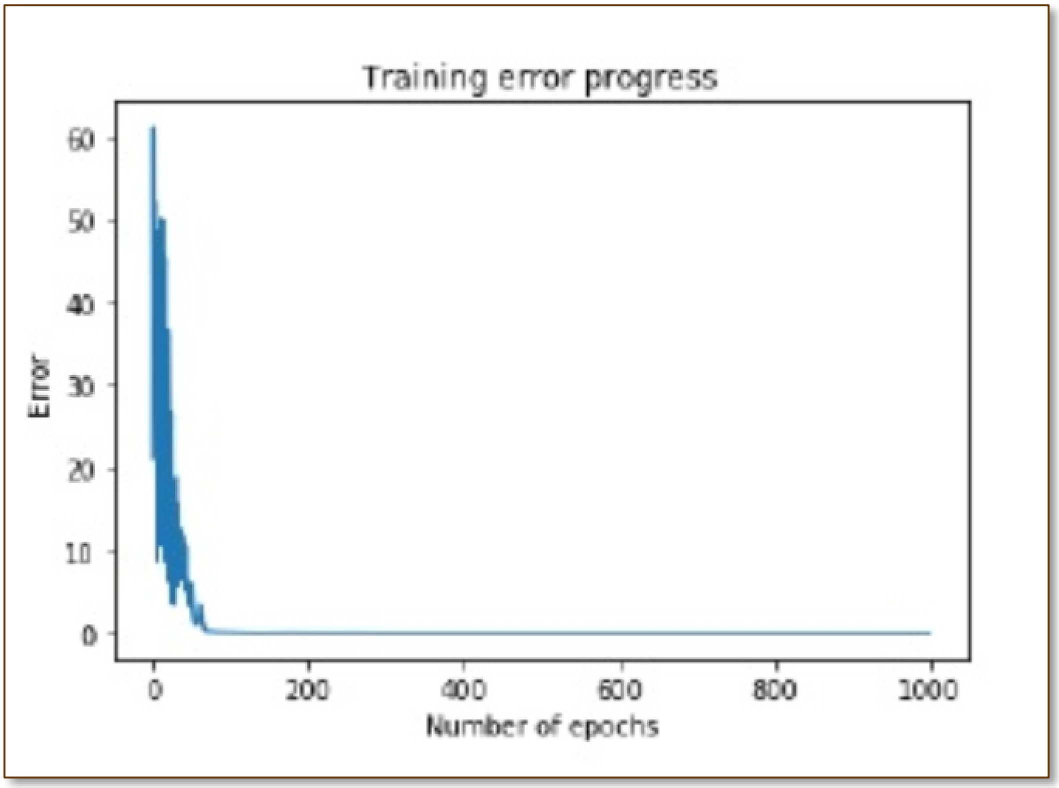
Now we will be plotting the actual versus predicted output:

```
x_dense = np.linspace(min_val, max_val, num_points * 2)
y_dense_pred =
neural_net.sim(x_dense.reshape(x_dense.size,1)).reshape(x_dense.size)
plt.figure()
plt.plot(x_dense, y_dense_pred, '-', x, y, '-', x, y_pred, 'p')
plt.title('Actual vs predicted')
plt.show()
```

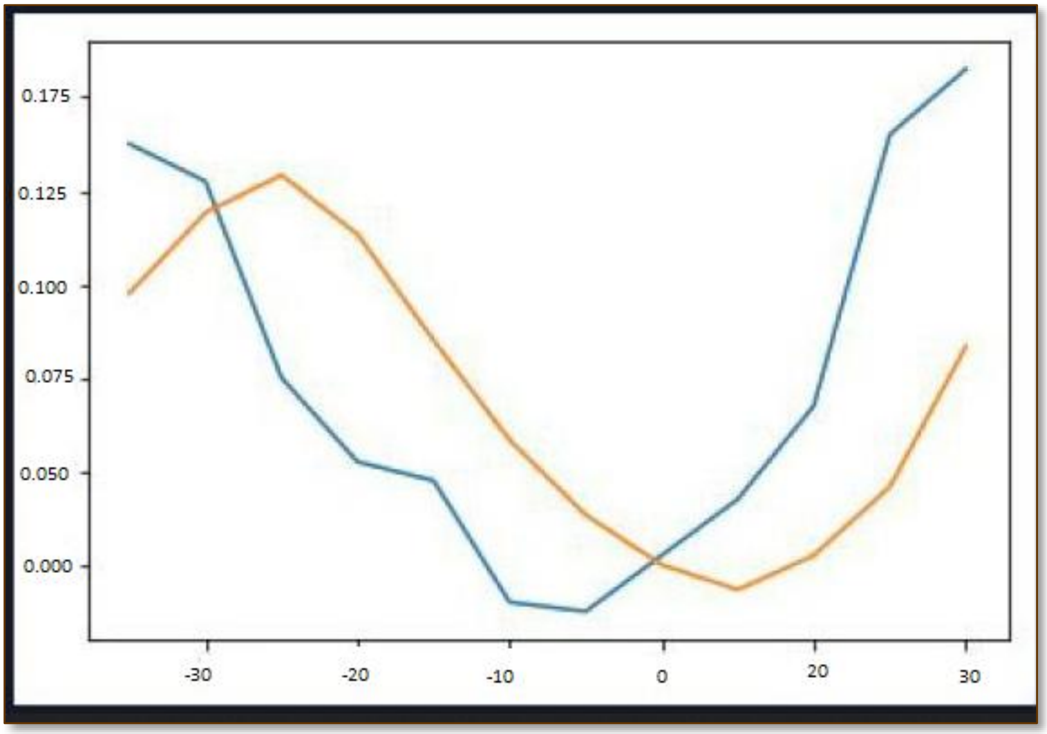
As a result of the above commands, you can observe the graphs as shown below



Multi-Layer Neural Networks



Multi-Layer Neural Networks: Training error



Multi-Layer Neural Networks: Actual vs Predicted

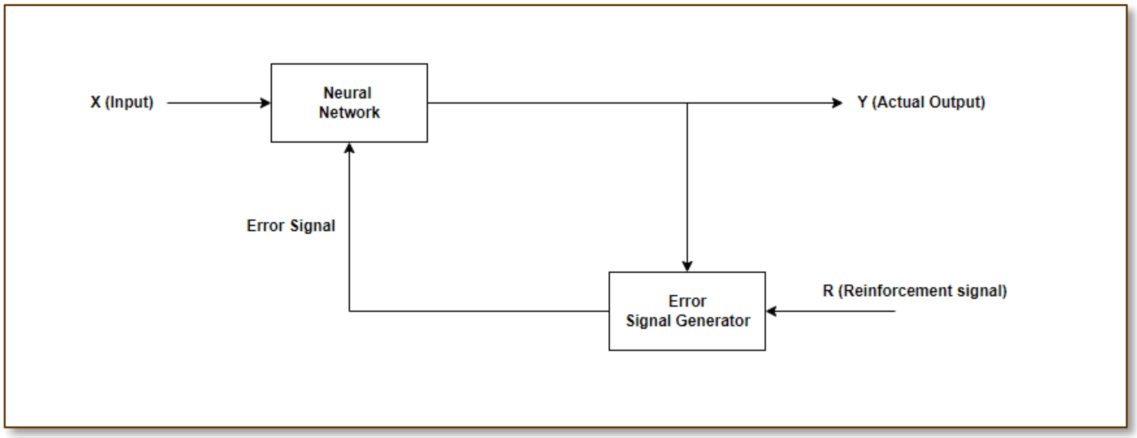
16 Reinforcement Learning

In this chapter, you will learn in detail about the concepts of reinforcement learning in AI with Python.

16.1 Basics of Reinforcement Learning

This type of learning is used to reinforce or strengthen the network based on critical information. That is a network being trained under reinforcement learning, receives some feedback from the environment. However, the feedback is evaluative and not instructive as in the case of supervised learning. Based on this feedback, the network performs the adjustments of the weights to obtain better critical information in the future.

This learning process is similar to supervised learning but we might have very less information. The following figure gives the block diagram of reinforcement learning:



Reinforcement Learning

16.2 Building Blocks: Environment and Agent

Environment and Agent are the main building blocks of reinforcement learning in AI. This section discusses them in detail:

Agent

An agent is anything that can perceive its environment through sensors and acts upon that environment through effectors.

- A **human agent** has sensory organs such as *eyes, ears, nose, tongue,* and *skin parallel* to *the sensors*, and other organs such as *hands, legs, and moth, for effectors*.
- A **robotic agent** replaces cameras and infrared range finders for the sensors, and various motors and actuators for effectors.
- A **software agent** has encoded bit strings as its programs and actions.

Agent Terminology

The following terms are more frequently used in reinforcement learning in AI:

- **Performance Measure of Agent**: It is the criteria, which determines how successful an agent is.
- **Behaviour of Agent**: It is the action that the agent performs after any given sequence of percepts.
- **Percept**: It is the agent's perceptual inputs at a given instance.
- **Percept Sequence**: It is the history of all that an agent has perceived to date.
- **Agent Function**: It is a map from the precept sequence to an action.

Environment

Some programs operate in an entirely **artificial environment** confined to keyboard input, database, computer file systems, and character output on a screen.

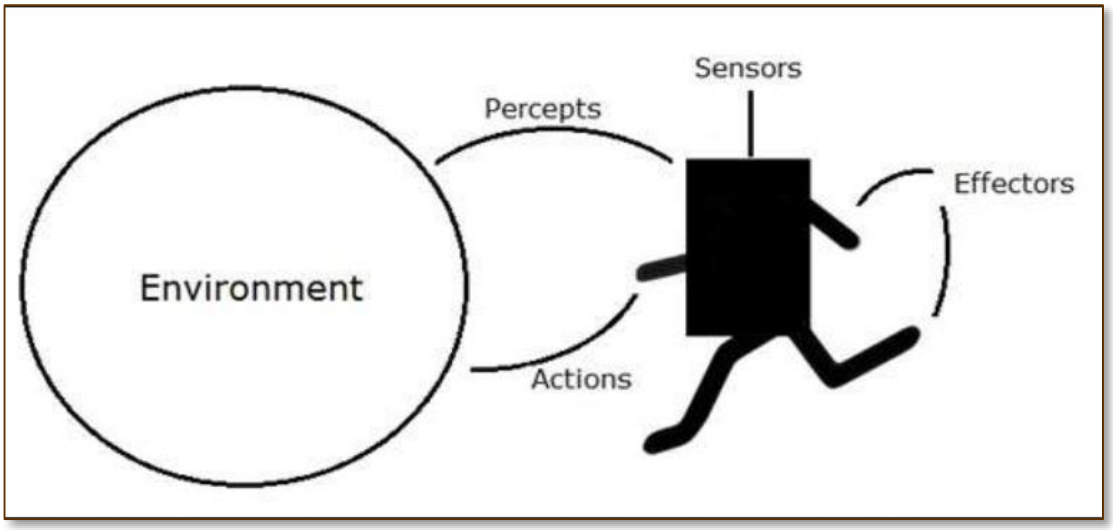
In contrast, some software agents, such as software robots or softbots, exist in rich and unlimited softbots domains. The simulator has a **very detailed**, and **complex environment**. The software agent needs to choose from a long array of actions in real-time.

For example, a softbot designed to scan the online preferences of the customer and display interesting items to the customer works in the **real** as well as an **artificial** environment.

Properties of Environment

The environment has multifold properties as discussed below:

- **Discrete/Continuous**: If there are a limited number of distinct, clearly defined, states of the environment, the environment is discrete, otherwise it is continuous. For example, chess is a discrete environment and driving is a continuous environment.
- **Observable/Partially Observable**: If it is possible to determine the complete state of the environment at each time point from the percepts, it is observable, otherwise it is only partially observable.
- **Static/Dynamic**: If the environment does not change while an agent is acting, then it is static; otherwise it is dynamic.
- **Single agent/Multiple agents**: The environment may contain other agents which may be of the same or different kind as that of the agent.
- **Accessible/Inaccessible**: If the agent's sensory apparatus can have access to the complete state of the environment, then the environment is accessible to that agent, otherwise it is inaccessible.
- **Deterministic/Non-deterministic**: If the next state of the environment is completely determined by the current state and the actions of the agent, then the environment is deterministic, otherwise it is non-deterministic.
- **Episodic/Non-episodic**: In an episodic environment, each episode consists of the agent perceiving and then acting. The quality of its action depends just on the episode itself. Subsequent episodes do not depend on the actions in the previous episodes. Episodic environments are much simpler because the agent does not need to think ahead.



Environment and Agent

16.3 Constructing an Environment with Python

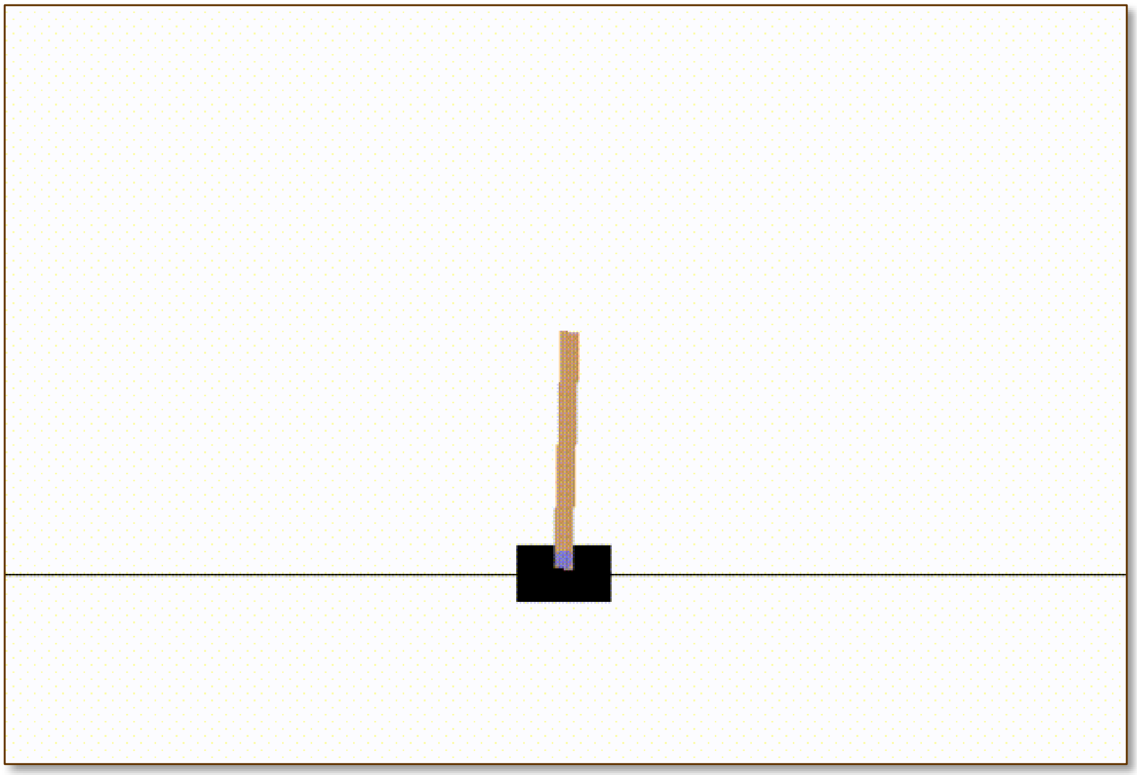
For building reinforcement learning agents, we will be using the **OpenAI Gym** package which can be installed with the help of the following command:

```
pip install gym
```

There are various environments in OpenAI gym that can be used for various purposes. A few of them are **Cartpole-v0**, **Hopper-v1**, and **MsPacman-v0**. They require different engines. The detailed documentation of **OpenAI Gym** can be found at `https://gym.openai.com/docs/#environments.`

The following code shows an example of Python code for the carpool-v9 environment:

```
import gym
env = gym.make('CartPole-v0')
env.reset()
for _ in range(1000):
    env.render()
    env.step(env.action_space.sample())
```



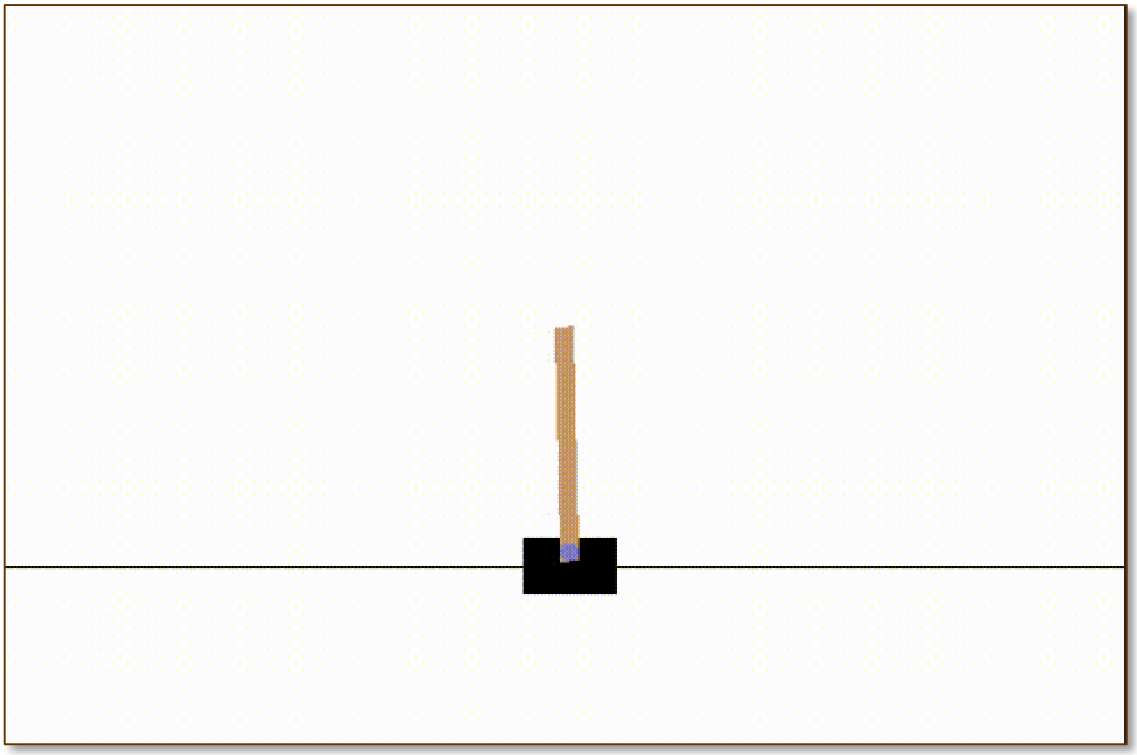
Example of Python code for carpool-v9

You can construct other environments in a similar way.

16.4Constructing a learning agent with Python

For building a reinforcement learning agent, we will be using the **OpenAI Gym** package as shown:

```
import gym
env = gym.make('CartPole-v0')
for _ in range(20):
    observation = env.reset()
    for i in range(100):
      env.render()
      print(observation)
      action = env.action_space_sample()
      observation, rewards, done, info = env.step(action)
      if done:
        print("Episode finished after () timesteps".format(i+1))
        break
```



Example of Python code for carpool-v9 - 2

Observe that the carpool can balance itself.

17 Genetic Algorithms

This chapter discusses the Genetic Algorithms of AI in detail.

17.1 What are Genetic Algorithms?

Genetic Algorithms (GAs) are search-based algorithms based on the concepts of natural selection and genetics. GAs are a subset of a much larger branch of computation known as Evolutionary Computation.

GAs was developed by John Holland and his students and colleagues at the University of Michigan, most notably David E. Goldberg. It has since been tried on various optimization problems with a high degree of success.

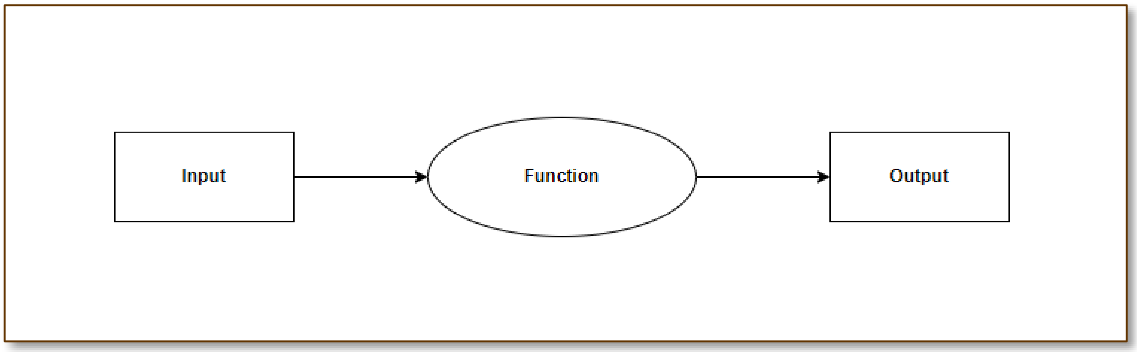
In GAs, we have a pool of possible solutions to the given problem. These solutions then undergo recombination and mutation (*like in natural genetics*), produce new children, and the process is repeated for various generations. Each individual (*or candidate solution*) is assigned a fitness value (*based on its objective function value*) and the fitter individuals are given a higher chance to mate and yield **fitter** individuals. This is in line with the Darwinian Theory of **Survival of the Fittest**.

Thus, it keeps **evolving** better individuals or solutions over generations, till it reaches a stopping criterion.

Genetic Algorithms are sufficiently randomized in nature, but they perform much better than random local search (*where we just try random solutions, keeping track of the best so far*), as they exploit historical information as well.

17.2 How to Use GA for Optimization Problems?

Optimization is an action of making design, situation, resource, and system, as effective as possible. The following block diagram shows the optimization process:



Use GA for Optimization

Stage of GA mechanism for optimization process The following is a sequence of steps of GA mechanism when used for the optimization of problems:

- **Step 1** - Generate the initial population randomly.
- **Step 2** - Select the initial solution with the best fitness values.
- **Step 3** - Recombine the selected solutions using mutation and crossover operators.
- **Step 4** - Insert an offspring into the population.
- **Step 5** - Now, if the stop conditions are met, return the solution with its best fitness value. Else go to step 2.

17.3 Installing Necessary Packages

For solving the problem by using *Genetic Algorithms* in Python, we are going to use a powerful package for GA called **DEAP**. It is a libary of novel evolutionary computation frameworks for rapid prototyping and testing of ideas. We can install this package with the help of the following command on the command prompt:

```
pi install deap
```

If you are using an **anaconda** environment, then the following command can be used to install deap:

```
conda install -c conda-forge deap
```

17.4Implementing Solutions using Genetic Algorithms

This section explains you the implementation of solutions using Genetic Algorithms.

Generating bit patterns The following example shows you how to generate a bit string that would contain 15 ones, based on the **One Max** problem.

Import the necessary packages as shown:

```
import random
from deap import base, creator, tools
```

Define the evaluation function. It is the first step to creating a genetic algorithm.

```
def eval_func(individual):
    target_sum = 15
    return len(individual) - abs(sum(individual) - target_sum),
```

Now, create the toolbox with the right parameters:

```
def create_toolbox(num_bits):
    creator.create("FitnessMax", base.Fitness, weights = (1.0,))
    creator.create("Individual, list, fitness=creator.FitnessMax)
```

Initialize the toolbox:

```
    toolbox = base.Toolbox()
toolbox.register("attr_bool", random.randint, 0, 1)
toolbox.register("individual", tools.initRepeat, creator.Individual,
    toolbox.attr_bool, num_bits)
toolbox.register("population", tools.initRepeat, list,
toolbox.individual)
```

Register the evaluation operator:

```
toolbox.register("evaluate", eval_func)
```

Now, register the crossover operator:

```
toolbox.register("mate", tools.cxTwoPoint)
```

Register a mutation operator:

```
toolbox.register("mutate", tools.mutFlipBit, indpb = 0.05)
```

Define the operator for breeding:

```
toolbox.register("select", tools.selTournament, tournsize = 3)
return toolbox
if __name__ == "__main__":
    num_bits = 45
    toolbox = create_toolbox(num_bits)
    random.seed(7)
    population = toolbox.population(n = 500)
    probab_crossing, probab_mutating = 0.5, 0.2
    num_generations = 10
    print('\nEvaluated', len(population), 'individuals')
```

Create and iterate through generations:

```
for g in range(num_generations):
    print("\n- Generation", g)
```

Selecting the next generation individuals

```
offspring = list(map(toolbox.clone, offspring))
```

Apply crossover and mutation on the offspring:

```
for chid1, child 2 in zip[::2], offspring[1::2]:
    if random.random() < probab_crossing:
    toolbox.mate(child1, child 2)
```

Delete the fitness value of child:

```
def child1.fitness.values
def child2.fitness.values
```

Now, apply mutation:

```
for mutant in offspring:
    if random.random() < probab_mutating:
    toolbox.mutate(mutant)
    del mutant.fitness.values
```

Evaluate the individuals with an invalid fitness:

```
invalid_ind = [ind for ind in offspring if not ind.fitness.valid]
fitnesses = map(toolbox.evaluate, invalid_ind)
for ind, fit in zip(invalid_ind, fitnesses):
    ind.fitness.values = fit
print('Evaluated', len(invalid_ind), 'invdividuals')
```

Now, replace population with next generation individual:

```
population[:] = offspring
```

Print the statistics for the current generations:

```
fits = [ind.fitness.values[0] for ind in population]
length = len(population)
mean = sum(fits) / length
sum2 = sum(x*x for x in fits)
std = abs(sum2 / length - mean**2)**0.5
print('Min =', min(fits), ', Max =', max(fits))
print('Average = ', round(mean, 2), ', Standard deviation =',
round(std, 2))
print("\n- Evolution ends")
```

Print the final output:

```
    best_ind = tools.selBest(population, 1)[0]
    print('\nBest individual:\n', best_ind)
    print('\nNumber of ones:', sum(best_ind))
Following would be the output:
Evoltion process starts
Evaluated 500 individuals
- Generation 0
Evaluated 295 individuals
Min = 32.0, Max = 45.0
Average = 40.29 , Standard deviation = 2.61
- Generation 1
Evaluated 292 individuals
Min = 34.0 , Max = 45.0
Average = 42.35 , Standard deviation = 1.91
- Generation 2
Evaluated 277 individuals
Min = 37.0 , Max = 45.0
Average = 43.39 , Standard deviation = 1.46
- - - -
- Generation 9
Evaluated 299 individuals
Min = 40.0 , Max = 45.0
Average = 44.12 , Standard deviation = 1.11
- Evolution ends
Best individual:
[0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1,
 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0,
 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1,]
Number of ones: 15
```

Symbol Regression Problem It is one of the best known problems in genetic programming. All symbolic regression problems use an arbitrary data distribution, and try to fit the most accurate data with a symbolic formula. Usually, a measure like the *RMSE(Root Mean Square Error)* is used to measure an individual's fitness. It is a classic regressor problem and here we are using the equation **5x(3)-6x(2)+8x=1**. We need to follow all the steps as followed in the above example, but the main part would be to create the primitive sets because they are the building blocks for the individuals so the evaluation can start. Here we will be using the classic set of primitives.

The following Python code explains this in detail:

```
import operator
import math
import random
import numpy as np
from deap import algorithms, base, creator, tools, gp

def division_operator(numerator, denominator):
    if denominator == 0:
        return 1
    return numerator/denominator

def eval_func(individual, points):
    func = toolbox.compile(expr=individual)
    mse = ((func(x) - math.sin(x))**2 for x in points)
    return math.fsum(mse) / len(points),

def create_toolbox():
    pset = gp.PrimitiveSet("MAIN", 1)
    pset.addPrimitive(operator.add, 2)
    pset.addPrimitive(operator.sub, 2)
    pset.addPrimitive(operator.mul, 2)
    pset.addPrimitive(division_operator, 2)
    pset.addPrimitive(operator.neg, 1)
    pset.addPrimitive(math.cos, 1)
    pset.addPrimitive(math.sin, 1)
    pset.addEphemeralConstant("rand101", lambda: random.randint(-1, 1))
    pset.renameArguments(ARG0='x')

    creator.create("FitnessMin", base.Fitness, weights=(-1.0,))
    creator.create("Individual", gp.PrimitiveTree,
fitness=creator.FitnessMin)

    toolbox = base.Toolbox()
    toolbox.register("expr", gp.genHalfAndHalf, pset=pset, min_=1,
max_=2)
    toolbox.register("individual", tools.initIterate,
creator.Individual, toolbox.expr)
    toolbox.register("population", tools.initRepeat, list,
toolbox.individual)
    toolbox.register("compile", gp.compile, pset=pset)
    toolbox.register("evaluate", eval_func, points=[x/10. for x in
range(-10, 10)])
```

```
    toolbox.register("select", tools.selTournament, tournsize=3)
    toolbox.register("mate", gp.cxOnePoint)
    toolbox.register("expr_mut", gp.genFull, min_=0, max_=2)
    toolbox.register("mutate", gp.mutUniform, expr=toolbox.expr_mut,
pset=pset)
    toolbox.decorate("mate",
gp.staticLimit(key=operator.attrgetter("height"), max_value=17))
    toolbox.decorate("mutate",
gp.staticLimit(key=operator.attrgetter("height"), max_value=17))
    return toolbox

if __name__ == "__main__":
    random.seed(7)
    toolbox = create_toolbox()
    population = toolbox.population(n=450)
    hall_of_fame = tools.HallOfFame(1)
    stats_fit = tools.Statistics(lambda ind: ind.fitness.values)
    stats_size = tools.Statistics(len)
    mstats = tools.MultiStatistics(fitness=stats_fit, size=stats_size)
    mstats.register("avg", np.mean)
    mstats.register("std", np.std)
    mstats.register("min", np.min)
    mstats.register("max", np.max)

    probab_crossover = 0.4
    probab_mutate = 0.2
    number_gen = 10

    population, log = algorithms.eaSimple(population, toolbox,
probab_crossover, probab_mutate, number_gen,
                                          stats=mstats,
halloffame=hall_of_fame, verbose=True)
```

Note that all the basic steps are the same as used while generating bit patterns. This program will give us the output as min, max, and std (standard deviation) after 10 generations.

18 Computer Vision

Computer vision is concerned with modeling and replicating human vision using computer software and hardware. In this chapter, you will learn in detail about this.

18.1 Computer Vision

Computer vision is a discipline that studies how to reconstruct, interrupt and understand a **3d** scene from its **2d** images, in terms of the properties of the structure present in the scene.

Computer Vision Hierarchy

Computer vision is divided into three basic categories as follows:

- **Low-level vision**: it includes process images for feature extraction.
- **Intermediate-level vision**: It includes objective recognition and **3D** scene interpretation.
- **High-level vision**: It includes a conceptual description of a scene like activity, intention, and behavior.

18.2 Computer Vision Vs Image Processing

Image processing studies image-to-image transformation. The input and output of image processing are both images.

computer vision is the construction of explicit, meaningful descriptions of physical objects from their image. The output of computer vision is a description or an interpretation of structures in a **3D** scene.

Applications

Computer vision finds applications in the following fields:

Robotics

- Localization-determine robot location automatically
- Navigation
- Obstacles avoidance
- Assembly (peg-in-hole, welding, painting)
- Manipulation (e.g. PUMA robot manipulator)
- Human-Robot Interaction (HRI): Intelligent robotics to interact with and serve people.

Medicine

- Classification and detection (e.g. lesion or cells classification and tumor detection)
- 2D/3D segmentation
- 3D human organ reconstruction (MRI or ultrasound)
- Vision-guided robotics surgery

Security

- Biometrics (iris, fingerprint, face recognition)
- Surveilance-detecting certain suspicious activities or behaviors

Transportation

- Autonomous vehicle
- Safety, e.g., driver vigilance monitoring

Industrial Automation Application

- Industrial inspection(defect detection)
- Assembly
- Barcode and package label reading
- Object sorting
- Document understanding (e.g, OCR)

18.3 Installing Useful Packages

For Computer vision with Python, you can use a popular library called **OpenCV** (*Open Source Computer Vision*). It is a library of programming functions mainly aimed at real-time computer vision. It is written in *C++* and its primary interface is in *C++*. You can install this package with the help of the following command:

```
pip install opncv_python-X.X-cp36-cp36m-winX.whl
```

Here X represents the version of Python installed on your machine as well as the *win32* or *64-bit* you are having.

If you are using the **anaconda** environment, then use the following command to install OpenCV:

```
conda install -c conda-forge opencv
```

18.4 Reading, Writing and Displaying an Image

Most of the CV applications need to get the images as input and produce the images as output. In this section, you will learn how to read and write an image file with the help of functions provided by OpenCV.

OpenCV functions for Reading, Showing, and Writing an Image File

OpenCV provides the following functions for this purpose:

- **imread()function**: This is the function for reading an image. OpenCV imread() supports various image formats like *PNG, JPEG, TIFF, etc*.
- **imshow()function**: This is the function for showing an image in a window. The window automatically fits the image size. OpenCV imshow() supports various image formats like *PNG, JPEG, JPG, TIFF, etc*.
- **imwrite()function**: This is the function for writing an image. OpenCV imwrite() supports various image formats like *PNG, JPEG, TIFF, etc*.

Example This example shows the Python code for reading an image in one format - showing it in a window and writing the same image in other formats. Consider the steps shown below:

Import the OpenCV package as shown:

```
import cv2
```

Now, for reading a particular image, use the **imread()** function:

```
image = cv2.imread('image_flower.jpg')
```

For showing the image, use the **imshow()** function. The name of the window in which you can see the image would be **image_flower**.

```
cv2.imshow('image_flower', image)
cv2.destroyAllwindows()
```

Example

Now, we can write the same image into the other format, say .png using the **imwrite()** function:

```
cv2.imwrite('image_flower.png', image)
```

The output True means that the image has been successfully written as .png file also in the same folder.

```
True
```

Note: The function **destroyallWindows()** simply destroy all the windows we created.

18.5 Color Space Conversion

In OpenCV, the images are not stored by using the conventional *RGB* color, rather they are stored in the reverse order i.e. in the *BGR* order. Hence the default color code while reading an image is *BGR*. The **cvtColor()** conversion function is for converting the image from one color code to other.

Example Consider this example to convert an image from *BGR* to grayscale.

Import **OpenCV** package as shown:

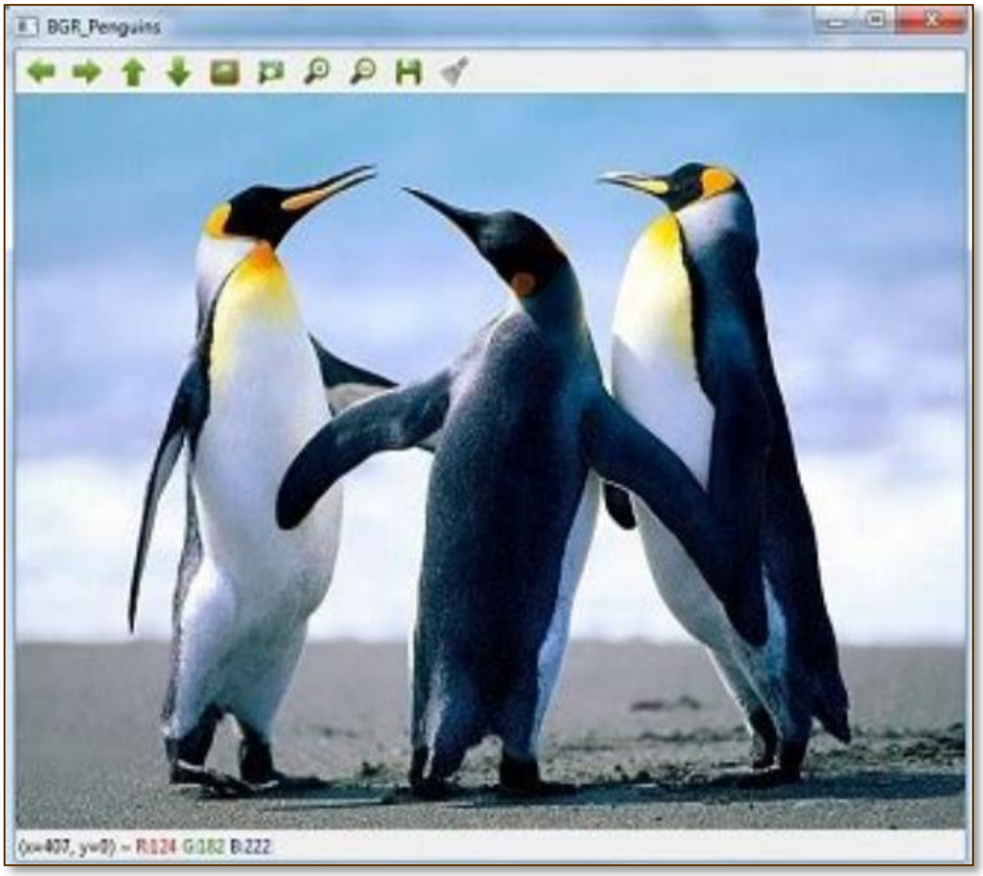
```
import cv2
```

Now, for reading a particular image, use the **imread()** function:

```
image = cv2.imread('image_flower.jpg')
```

Now, if we see this image using the **imshow()** function, then we can see that this image is in BGR.

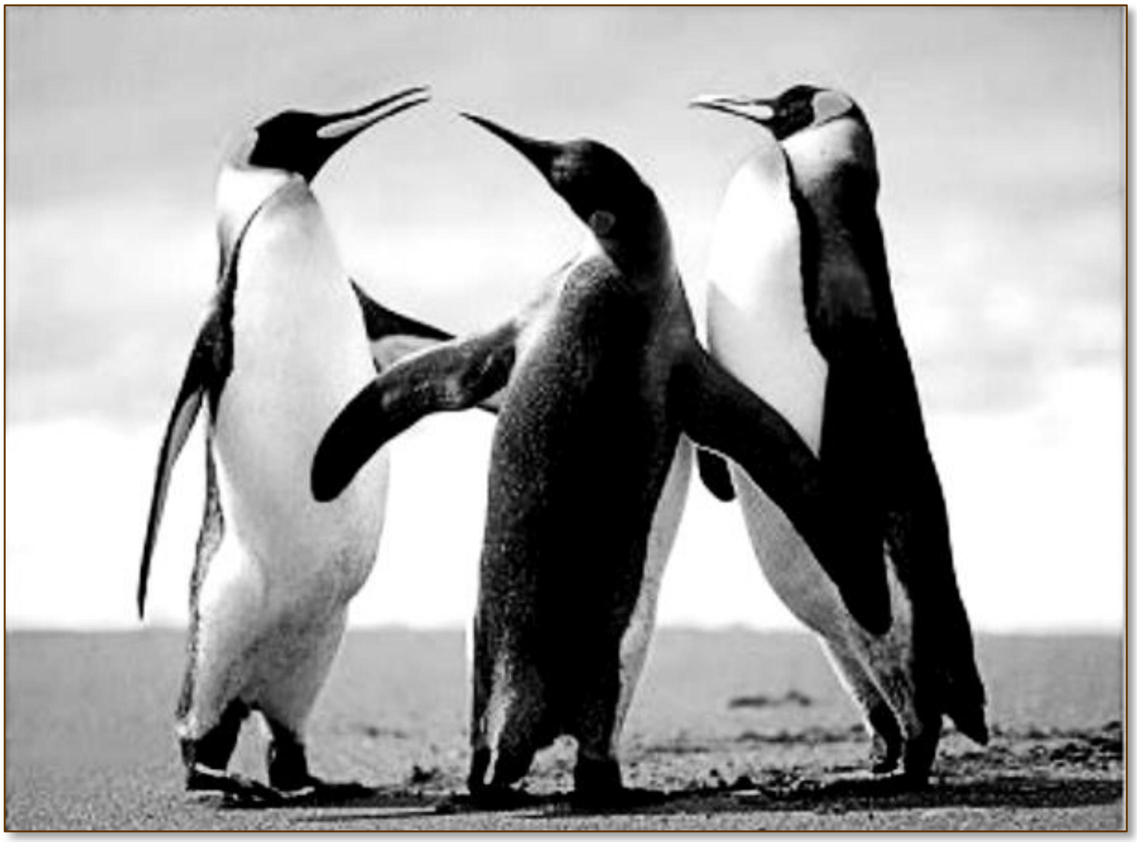
```
cv2.imshow('BGR_Penguins", image)
```



BGR Penguins

Now, use **cvtColor()** function to convert this image to grayscale.

```
image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
cv2.imshow('gray_penguins', image)
```



BGR Penguins - gray

18.6 Edge Detection

Humans, after seeing a rough sketch, can easily recognize many object types and their poses. That is why edges play an important role in the life of humans as well as in the applications of computer vision. OpenCV provides a very simple and useful function called **Canny()** for detecting the edges.

Example The following example shows clear identification of the edges.

Import OpenCV package as shown:

```
import cv2
import numpy as np
```

Now, for reading a particular image, use the **imread()** function.

```
image = cv2.imread('Penguins.jpg')
```

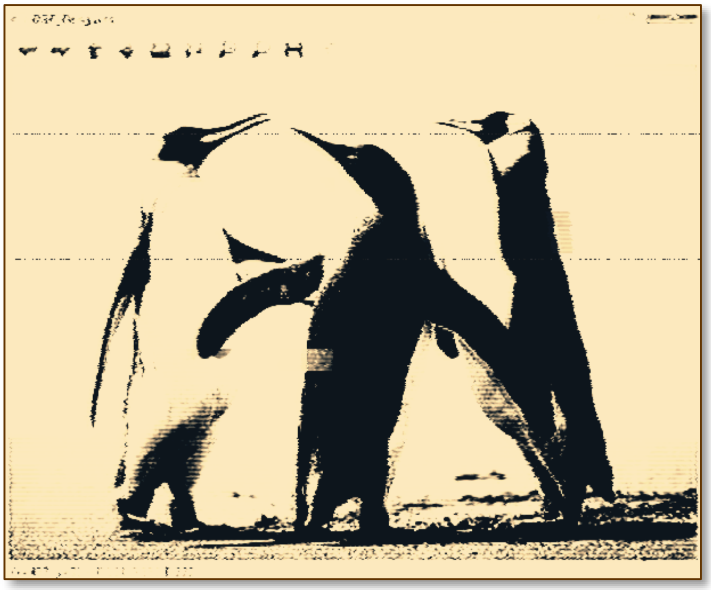
Now, use the **Canny()** function for detecting the edge of the already read image.

```
cv.imwrite('edges_Penguins.jpg', cv2, Canny(image,200, 300))
```

Now, for showing the image with edges, use the **imshow()** function.

```
cv2.imshow('edges', cv2.imread(''exdges_Penguins.jpg'))
```

This Python program will creat an image named **edges_penguins.jpg** with edge detection.



BGR Penguins - edge detection

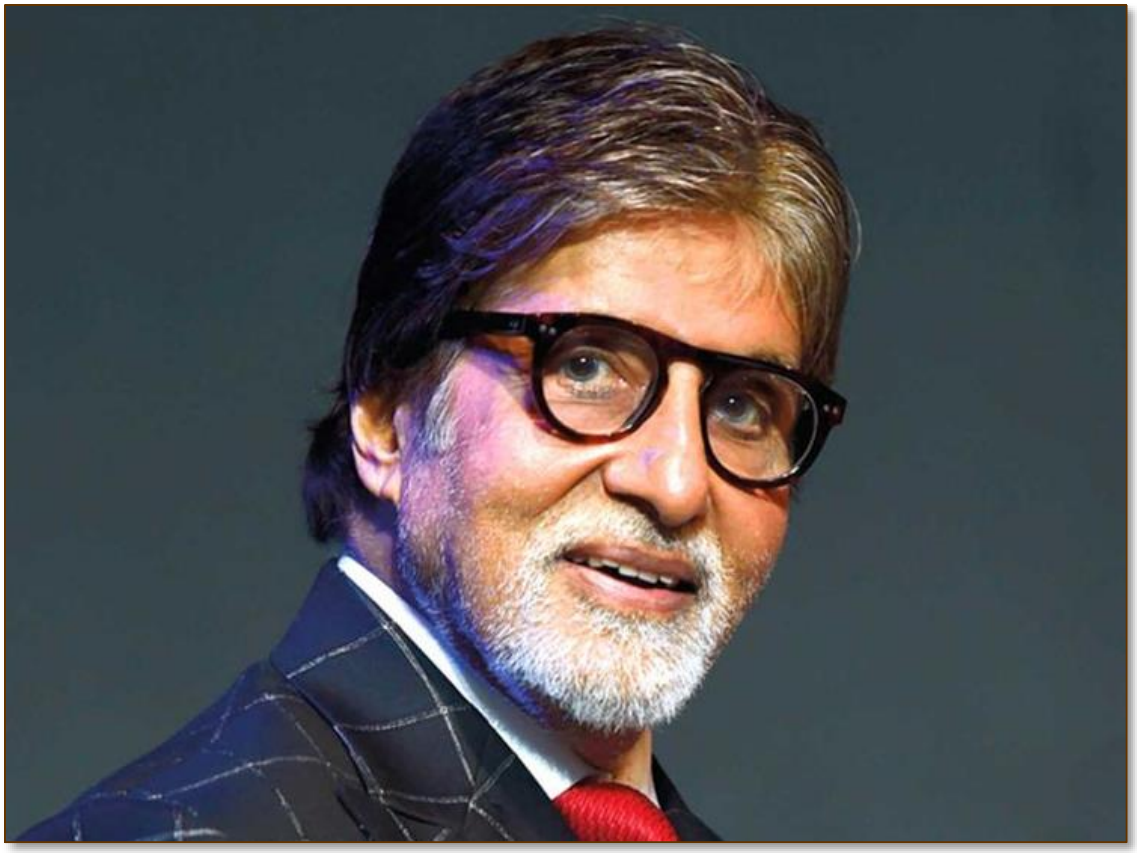
18.7 Face Detection

Is one of the fascinating applications of computer vision which makes it more realistic as well as futuristic. OpenCV has a built-in facility to perform face detection. We are going to use the **Haar** cascade classifier for face detection.

Haar Cascade Data

We need data to use the Haar cascade classifier. YOu can find this data in our OpenCV package. After installing OpenCV, you can see the folder name **haarcascades**. There would be .xml files for different applications. Now, copy all of them for different use and paste them into a new folder under the current project.

Example The following is the Python code using Haar Cascade to detect the face of Amitabh Bachan shown in the following image:



Haar Cascade

Import the **OpenCV** package as shown:

```
import cv2
import numpy as np
```

Now, use the **HaarCascadeClassifier** for detecting face:

```
face_detection=
cv2.CascadeClassifier('D:/ProgramData/cascadeclassifer/
haarcascade_frontalface_default.xml')
```

Now, for reading a particular image, use the **imread()** function:

```
img = cv2.imread('AB.jpg')
```

Now, convert it into grayscale because it would accept gray images:

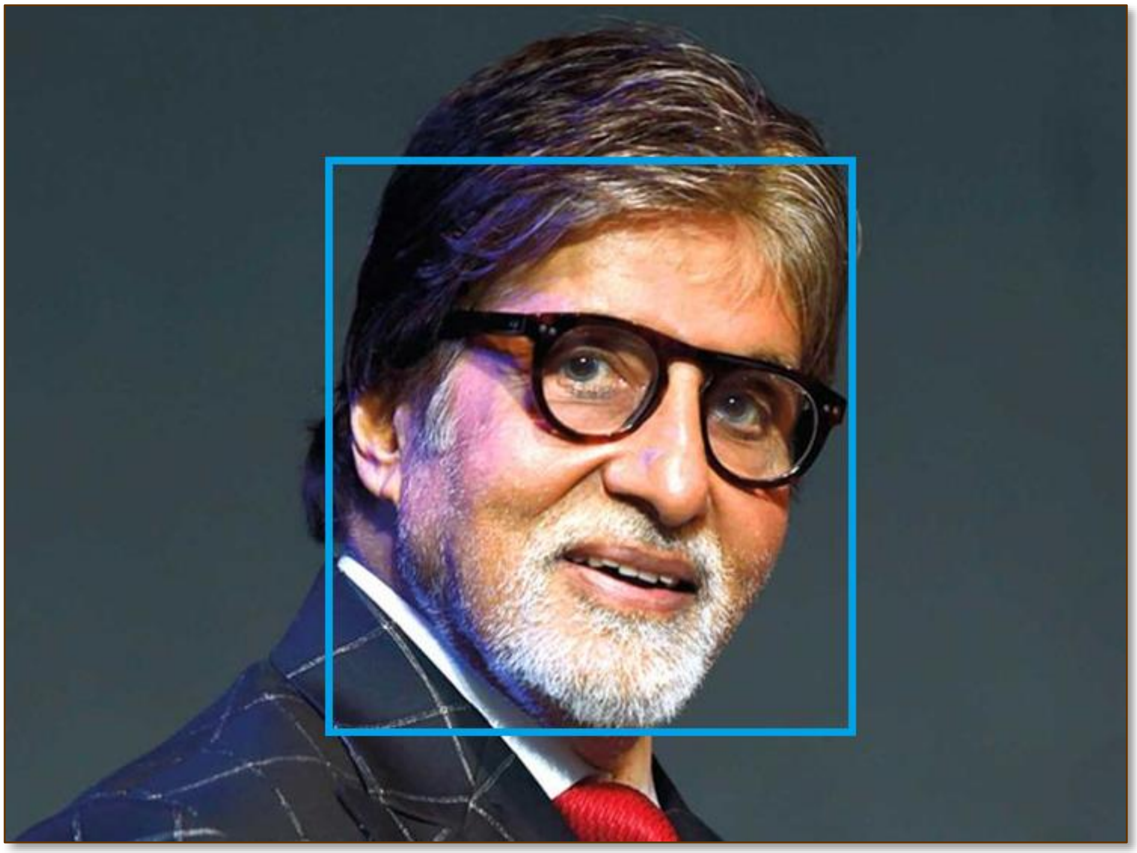
```
gray = cv2.cvtColor(img, cv2, COLOR_BGR2GRAY)
```

Now, using **face_detection.detectMultiScale**, perform actual face detection:

```
faces = face_detection.detectMultiScale(gray, 1.3, 5)
```

Now, draw a rectangle around the whole face:

This Python program will create an image named **Face_AB.jpg** with face detection as shown:

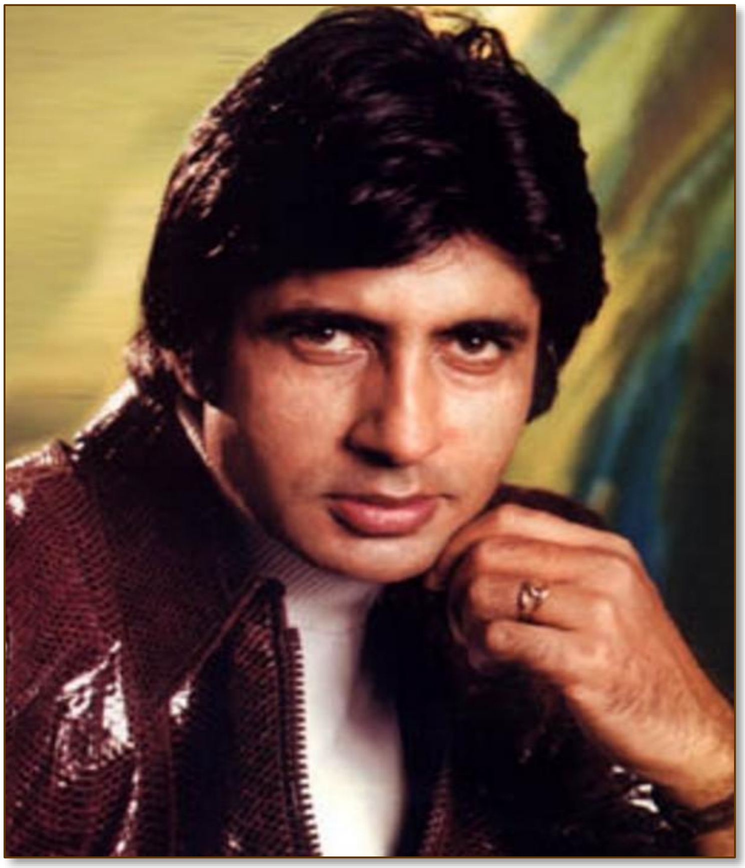


Haar Cascade - Face A/B

18.8 Eye Detection

Is another fascinating application of computer vision which makes it more realistic as well as futuristic. OpenCV has a built-in facility to perform eye detection. We are going to use the **Haar cascade** classifier for eye detection.

Example The following example gives the Python code using Haar Cascade to detect the face of Amitabh Bachan.



Eye Detection

Import OpenCV package as shown:

```
import cv2
import numpy as np
```

Now, use the **HaarCascadeClassifier** for detecting face:

```
eye_cascade =
cv2.CascadeClassifier('D:/ProgramData/cascadeclassifier/haarcascade_eye
.xml)
```

Now, for reading a particular image, use the **imread()** function:

```
img = cv2.imread('AB_Eye.jpg')
```

Now, convert it into grayscale because it would accept grey images:

```
gray = cv2.cvtColor(img, cv2.COLOR_BGRGRAY)
```

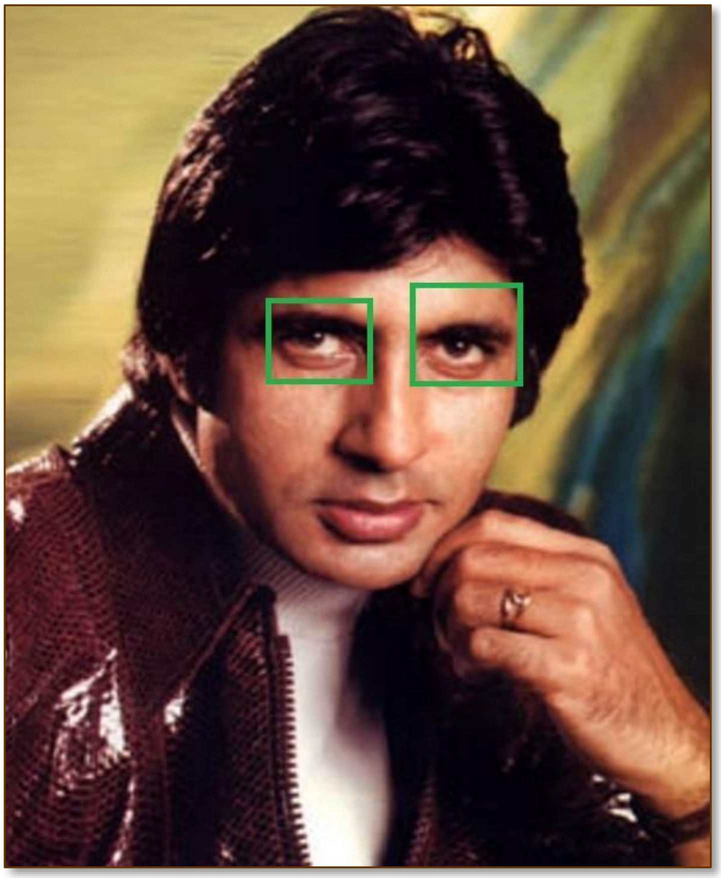
Now with the help of **eye_cascade.detectMultiScale** performs actual face detection:

```
eyes = eye_cascade.detectMultiScale(gray, 1.03, 5)
```

Now, draw a rectangle around the whole face:

```
for (ex,ey,ew,eh) in eyes:
    img = cv2.rectangle(img,(ex,ey),(ex+ew, ey+eh), (0,255,0), 2)
cv2.imwrite('Eye_AB.jpg, img)
```

This Python program will create an image named **Eye_AB.jpg** with eye detection as shown:



Eye AB

19 Deep Learning

Artificial Neural Network (ANN) is an efficient computing system, whose central theme is borrowed from the analogy of biological neural networks. Neural networks are one type of model for machine learning. In the mid-1980s and early 1990s, many important architectural advancements were made in neural networks. In this chapter, you will learn more about Deep Learning, an approach of AI.

Deep learning emerged from a decade's explosive computational growth as a serious contender in the field. Thus, deep learning is a particular kind of machine learning whose algorithms are inspired by the structure and function of the human brain.

19.1 Machine Learning v/s Deep Learning

Is the most powerful machine learning technique these days. It is so powerful because they learn the best way to represent the problem while learning how to solve the problem. A comparison of Deep learning and Machine learning is given below:

Data Dependency

The first point of difference is based on the performance of DL and ML when the scale of data increases. When the data is large, deep learning algorithms perform very well.

Machine Dependency

Deep learning algorithms need high-end machines to work perfectly. On the other hand, machine learning algorithms can work on low-end machines too.

Feature Extraction

Deep learning algorithms can extract high-level features and try to learn from the same too. On the other hand, an expert is required to identify most of the features extracted by machine learning.

Time of Execution

Execution time depends upon the numerous parameters used in an algorithm. Deep learning has more parameters than machine learning algorithms. Hence, the execution time of DL algorithms, especially the training time, is much more than ML algorithms. But the testing time of DL algorithms is less than ML algorithms.

Approach to Problem-Solving

Deep learning solves the problem end-to-end while machine learning uses the traditional way of solving the problem i.e. by breaking down it into parts.

19.2Convolutional Neural Network (CNN)

Convolutional neural networks are the same as ordinary neural networks because they are also made up of neurons that have learnable weights and biases. Ordinary neural networks ignore the structure of input data and all the data is converted into a 1-D array before feeding it into the network. This process suits the regular data, however, if the data contains images, the process may be cumbersome.

CNN solves the problem easily. It takes the 2D structure of the images into account when they process them, which allows them to extract the properties specific to images. In this way, the main goal of CNNs is to go from the raw image data in the input layer to the correct class in the output layer. The only difference between ordinary NNs and CNNs is in the treatment of input data and in the type of layers.

Architecture Overview of CNNs

Architecturally, ordinary neural networks receive input and transform it through a series of hidden layers. Every layer is connected to the other layer with the help of neurons. The main disadvantage of ordinary neural networks is that they do not scale well to full images.

The architecture of CNNs has neurons arranged in 3 dimensions called width, height, and depth. Each neuron in the current layer is connected to a small patch of output from the previous layer. It is similar to overlaying an **NxN** filter on the input image. It uses **M** filters to be sure about getting all the details. These **M** filters are feature extractors that extract features like edges, corners, etc.

Layers used to construct CNNs

Following layers are used to construct CNNs:

- **Input Layer**: It takes the raw image data as it is.
- **Convolutional Layer**: This layer is the core building block of CNNs that does most of the computations. This layer computes the convolutions between the neurons and the various patches in the input.
- **Rectified Linear Unit Layer**: It applies an activation function to the output of the previous layer. It adds non-linearly to the network so that it can generalize well to any type of function.
- **Pooling Layer**: Pooling helps us to keep only the important parts as we progress in the network Pooling layer operates independently on every depth slice of the input and resizes it spatially. It uses the MAX function.
- **Fully Connected layer/Output layer**: This layer computes the output scores in the last layer. The resulting output is of the size **1X1XL**, where L is the number of training dataset classes.

19.3 Installing Useful Python Packages

You can use **Keras**, which is a high-level neural networks API, written in Python and capable of running on top of *TensorFlow, CNTK*, or *Theno*. It is compatible with Python *2.7-3.6*. You can learn more about it from `https://keras.io/`

Use the following commands to install keras:

```
pip install keras
```

On the **conda** environment, you can use the following command:

```
code install -c conda-forge keras
```

19.4 Building Linear Regressor using ANN

In this section, you will learn how to build a linear regressor using artificial neural networks. You can use **KerasRegressor** to archive this. In this example, we are using the Boston house price dataset with 13 numerals for properties in Boston. The Python code for the same is shown here:

Import all the required packages as shown:

```
import numpy
import pandas
from kera.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
```

Now, load our dataset which is saved in the local directory.

```
dataframe = pandas.read_csv("/Usrrs/admin/data.csv", delim_whitespace =
True, header = None)
dataset = dataframe.values
```

Now, divide the data into input and output variables i.e. **X** and **Y**:

```
X = dataset[:,0:13]
Y = dataset[:,13]
```

Since we use baseline neural networks, define the model:

```
def baseline_model():
```

Now, create the model as follows:

```
model_regressor = Sequential()
model_regressor.add(Dense(13, input_dim = 13, kernel_initializer =
'normal',
    activation = 'reju'))
model_regressor.add(Dense(1, kernel_nitializer = 'normal'))
```

Next, compile the model:

```
model_regressor.compile(loss='mean_squared_error', optimizer = 'adam')
return model_regressor
```

Now, fix the random seed for reproducibility as follows:

```
seed = 7
numpy.random.seed(seed)
```

The Keras wrapper object for use in **scikit-learn** as a regression estimator is called **KerasRegressor**. In this section, we shall evaluate this model with the standardized data set.

```
estimator = KerasRegressor(build_fn = baseline_model, nb_epoch = 100,
batch_size = 5, verbose =0)
kfold = KFold(n_splits = 10, random_state = seed)
baseline_result = cross_val_score(estimator, X, Y, cv = kfold)
print("Baseline: %.2f (%.2f) MSE" % (Baseline_result.mean(),
Baseline_result.std()))
```

The output of the code shown above would be the estimate of the model's performance on the problem for unseen data. It will be the mean squared error, including the average and standard deviation across all 10 folds of the cross-validation evaluation.

19.5 Image Classifier: An Application of Deep Learning

Convolutional Neural Networks (CNNs) solve an image classification problem, that is to which class the input image belongs. You can use Keras deep learning libary. Note that we are using the training and testing data set of images of cats and dogs from the following link `https://www.kaggle.com/c/dogs-vs-cats/data`.

Import the important keras libraries and packages as shown:

The following package called sequential will initialize the neural networks as a sequential network.

```
from keras.models import Sequential
```

The following package called **Conv2D** is used to perform the convolution operation, the first step of CNN.

```
from keras.layers import Conv2D
```

The following package called **MaxPoling2D** is used to perform the pooling operation, the second step of CNN.

```
from keras.layers import MaxPooling2D
```

The following package called **Flatten** is the process of converting all the resultant 2D arrays into a single long continuous linear vector.

```
from keras.layers import Flatten
```

The following package called **Dense** is used to perform the full connection of the neural network, the fourth step of CNN.

```
from keras.layers import Dense
```

Now, create an object of the sequential class.

```
$_classifier = Sequential()
```

Now, the next step is coding the convolution part.

```
$_classifier.add(Conv2D(32, (3, 3), input_shape = (64, 64, 3),
activation = 'relu'))
```

Here **relu** is the rectifier functuion.

Now, the next step of CNN is the pooling operation on the pooling operation on the resultant feature maps after the convolution part.

```
$-classifier.add(MaxPooling2D(pool_size = (2, 2)))
```

Now, convert all the pooled images into a continuous vector by using flattering:

```
$_classifier.add(Flatten())
```

Next, create a fully connected layer.

```
$_classifier.add(Dense(units = 128, activation = 'relu'))
```

Here, *128* is the number of hidden units. It is a common practice to define the number of hidden units as the *power of 2*.

Now, initialize the output layer as follows:

```
$_classifier.add(Dense(units = 1, activation = 'sigmoid'))
```

Now, compile the CNN, we have built:

```
$_classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy',
metrics = ['accuracy'])
```

Here optimizer parameter is to choose the stochastic gradient descent algorithm, loss parameter is to choose the loss function and metrics parameter is to choose the performance metric.

Now, perform image augmentations and then fit the images to the neural networks:

```
train_detagen = ImageDataGenerator(rescale = 1./255, shear_range = 0.2,
zoom_range = 0.2
horizontial_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)

training_set =
    train_datagen.flow_from_directory("/Users/admin/training_set",
target_size =
        (64, 64), batch_size = 32, class_mode = 'binary')

test_set =
    test_datagen.flow_from_directory('test_set', target_size =
          (64, 64), batch_size = 32, class_mode = 'binary')
```

Now, fit the data to the model we have created:

```
classifier.fit_generator(training_set.step_per_epoch = 8000, epochs =
25,validation_data = test_set.validation_steps = 2000)
```

Here steps_per_epoch have the number of training images.

Now as the model has been trained, we can use it for prediction as follows:

```
from keras.preprocessing import image

test_image =
image.load_img('dataset/single_prediction/cat_or_dog_1.jpg',
target_size = (64, 64))

test_image = image.img_to_array(test_image)

test_image = np.expand_dims(test_image, axis = 0)

result = classifier.predict(test_image)

training_set.class_indices

if result[0][0] == 1:
prediction = 'dog'

else:
    prediction = 'cat'
```

20 Vision of Tommorow

As the technology evolves, it is crucial to remain mindful of the ethical implications of AI development and use. While AI has the potential to bring about great benefits, it can also be used in ways that violate individual rights and freedoms or perpetuate systemic biases. Therefore, it is important to develop and adhere to ethical standards and guidelines when working with AI. Another important consideration is the need for transparency and explainability in AI systems. As AI becomes more complex, it can be difficult to understand how it reaches certain decisions or recommendations. This can be particularly problematic in high-stakes applications such as healthcare or criminal justice. Therefore, researchers and developers should strive to create AI systems that are transparent and can be easily explained to end-users. In addition, it is important to recognize that AI is not a panacea for all problems. While it has the potential to solve complex problems, there are still some tasks that require human intuition and decision-making. Therefore, it is important to consider the limitations of AI and to use it in conjunction with human expertise to achieve the best results.One of the most exciting aspects of AI is its potential for innovation and discovery. By using AI algorithms to analyze large datasets or simulate complex systems, researchers can uncover patterns and relationships that were previously hidden. This can lead to new insights and discoveries in fields such as medicine, engineering, and physics, among others.