Machine Learning Notes

Machine learning is a growing technology which enables computers to learn automatically from past data. Machine learning uses various algorithms for building mathematical models and making predictions using historical data or information. Currently, it is being used for various tasks such as image recognition, speech recognition, email filtering, Facebook auto-tagging, recommender system, and many more.

What is Machine Learning

In the real world, we are surrounded by humans who can learn everything from their experiences with their learning capability, and we have computers or machines which work on our instructions. But can a machine also learn from experiences or past data like a human does? So here comes the role of **Machine Learning**.

Machine Learning is said as a subset of **artificial intelligence** that is mainly concerned with the development of algorithms which allow a computer to learn from the data and past experiences on their own. The term machine learning was first introduced by **Arthur Samuel** in **1959**. We can define it in a summarized way as:

> "Machine learning enables a machine to automatically learn from data, improve performance from experiences, and predict things without being explicitly programmed."

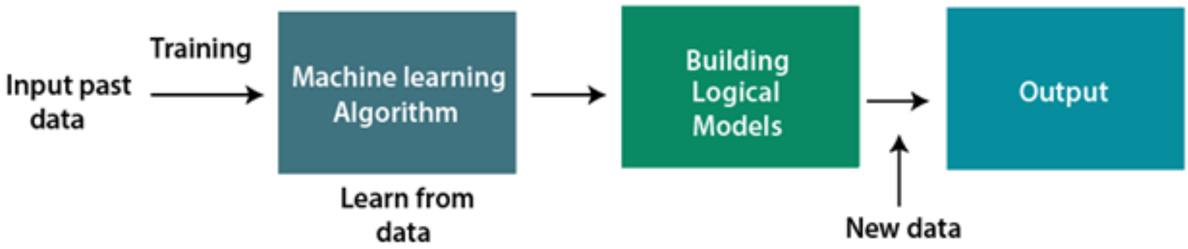
With the help of sample historical data, which is known as **training data**, machine learning algorithms build a **mathematical model** that helps in making predictions or decisions without being explicitly programmed. Machine learning brings computer science and statistics together for creating predictive models. Machine learning constructs or uses the algorithms that learn from historical data. The more we will provide the information, the higher will be the performance.

A machine has the ability to learn if it can improve its performance by gaining more data.

How does Machine Learning work

A Machine Learning system **learns from historical data, builds the prediction models, and whenever it receives new data, predicts the output for it**. The accuracy of predicted output depends upon the amount of data, as the huge amount of data helps to build a better model which predicts the output more accurately.

Suppose we have a complex problem, where we need to perform some predictions, so instead of writing a code for it, we just need to feed the data to generic algorithms, and with the help of these algorithms, machine builds the logic as per the data and predict the output. Machine learning has changed our way of thinking about the problem. The below block diagram explains the working of Machine Learning algorithm:



Features of Machine Learning:

- Machine learning uses data to detect various patterns in a given dataset.
- It can learn from past data and improve automatically.
- It is a data-driven technology.
- Machine learning is much similar to data mining as it also deals with the huge amount of the data.

Need for Machine Learning

The need for machine learning is increasing day by day. The reason behind the need for machine learning is that it is capable of doing tasks that are too complex for a person to implement directly. As a human, we have some limitations as we cannot access the huge amount of data manually, so for this, we need some computer systems and here comes the machine learning to make things easy for us.

We can train machine learning algorithms by providing them the huge amount of data and let them explore the data, construct the models, and predict the required output automatically. The performance of the machine learning algorithm depends on the amount of data, and it can be determined by the cost function. With the help of machine learning, we can save both time and money.

The importance of machine learning can be easily understood by its use cases, Currently, machine learning is used in **self-driving cars**, **cyber fraud detection**, **face recognition**, and **friend suggestion by Facebook**, etc. Various top companies such as Netflix and Amazon have built machine learning models that are using a vast amount of data to analyze the user interest and recommend product accordingly.

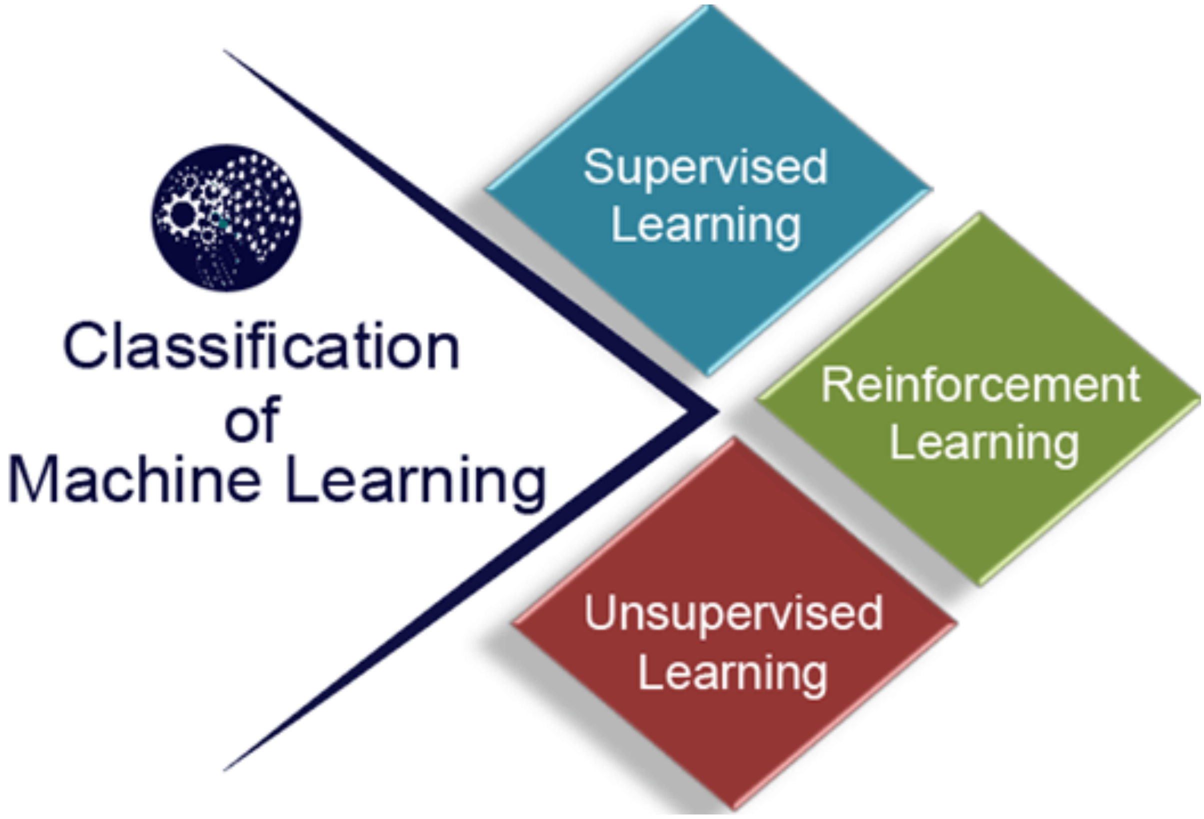
Following are some key points which show the importance of Machine Learning:

- Rapid increment in the production of data
- Solving complex problems, which are difficult for a human
- Decision making in various sector including finance
- Finding hidden patterns and extracting useful information from data.

Classification of Machine Learning

At a broad level, machine learning can be classified into three types:

1. **Supervised learning**
2. **Unsupervised learning**
3. **Reinforcement learning**



1) Supervised Learning

Supervised learning is a type of machine learning method in which we provide sample labeled data to the machine learning system in order to train it, and on that basis, it predicts the output.

The system creates a model using labeled data to understand the datasets and learn about each data, once the training and processing are done then we test the model by providing a sample data to check whether it is predicting the exact output or not.

The goal of supervised learning is to map input data with the output data. The supervised learning is based on supervision, and it is the same as when a student learns things in the supervision of the teacher. The example of supervised learning is **spam filtering**.

Supervised learning can be grouped further in two categories of algorithms:

- **Classification**
- **Regression**

2) Unsupervised Learning

Unsupervised learning is a learning method in which a machine learns without any supervision.

The training is provided to the machine with the set of data that has not been labeled, classified, or categorized, and the algorithm needs to act on that data without any supervision. The goal of unsupervised learning is to restructure the input data into new features or a group of objects with similar patterns.

In unsupervised learning, we don't have a predetermined result. The machine tries to find useful insights from the huge amount of data. It can be further classifieds into two categories of algorithms:

- **Clustering**
- **Association**

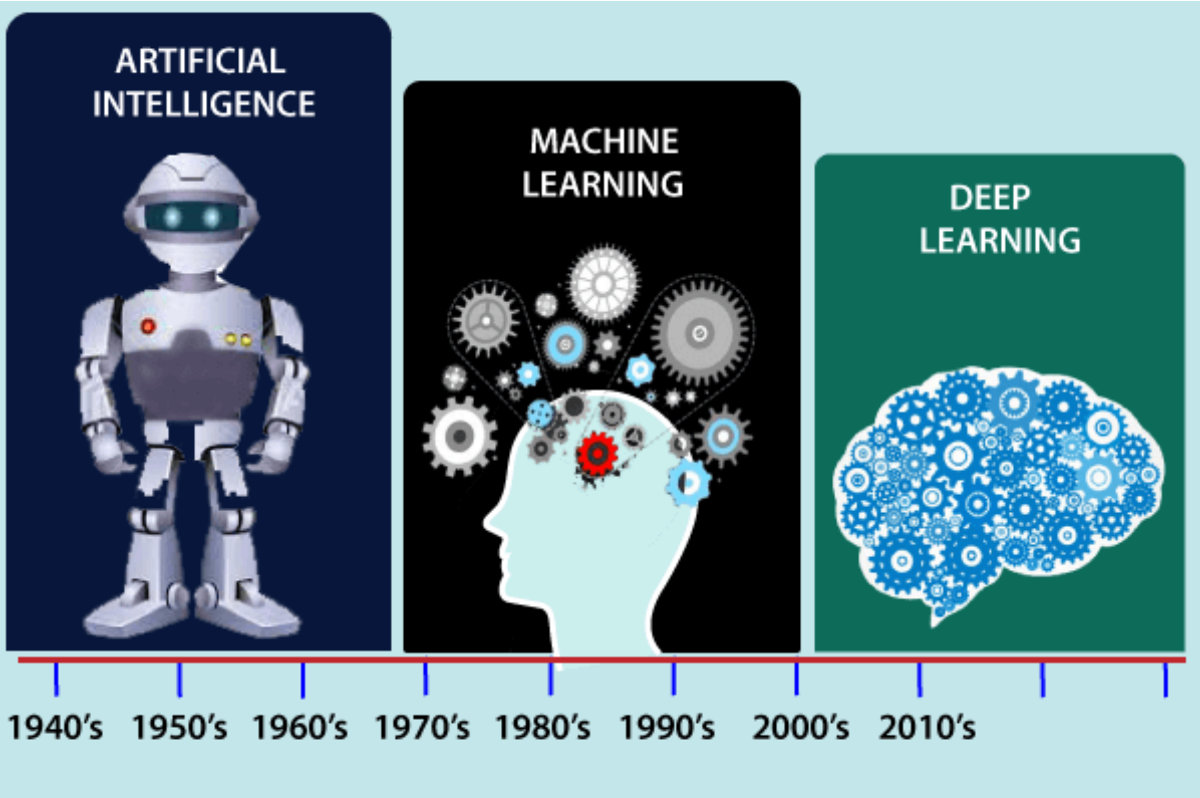
3) Reinforcement Learning

Reinforcement learning is a feedback-based learning method, in which a learning agent gets a reward for each right action and gets a penalty for each wrong action. The agent learns automatically with these feedbacks and improves its performance. In reinforcement learning, the agent interacts with the environment and explores it. The goal of an agent is to get the most reward points, and hence, it improves its performance.

The robotic dog, which automatically learns the movement of his arms, is an example of Reinforcement learning. Some other examples include: Personalised product recommendation system, Ad recommendation system, Self-driving cars (Motion planning including lane changing, parking), etc.

History of Machine Learning

Before some years (about 40-50 years), machine learning was science fiction, but today it is the part of our daily life. Machine learning is making our day to day life easy from **self-driving cars** to **Amazon virtual assistant "Alexa"**. However, the idea behind machine learning is so old and has a long history. Below some milestones are given which have occurred in the history of machine learning:



The early history of Machine Learning (Pre-1940):

- **1834:** In 1834, Charles Babbage, the father of the computer, conceived a device that could be programmed with punch cards. However, the machine was never built, but all modern computers rely on its logical structure.
- **1936:** In 1936, Alan Turing gave a theory that how a machine can determine and execute a set of instructions.

The era of stored program computers:

- **1940:** In 1940, the first manually operated computer, "ENIAC" was invented, which was the first electronic general-purpose computer. After that stored program computer such as EDSAC in 1949 and EDVAC in 1951 were invented.
- **1943:** In 1943, a human neural network was modeled with an electrical circuit. In 1950, the scientists started applying their idea to work and analyzed how human neurons might work.

Computer machinery and intelligence:

- **1950:** In 1950, Alan Turing published a seminal paper, "**Computer Machinery and Intelligence**," on the topic of artificial intelligence. **In his paper, he asked, "Can machines think?"**

Machine intelligence in Games:

- **1952:** Arthur Samuel, who was the pioneer of machine learning, created a program that helped an IBM computer to play a checkers game. It performed better more it played.
- **1959:** In 1959, the term "Machine Learning" was first coined by **Arthur Samuel**.

The first "AI" winter:

- The duration of 1974 to 1980 was the tough time for AI and ML researchers, and this duration was called as **AI winter**.
- In this duration, failure of machine translation occurred, and people had reduced their interest from AI, which led to reduced funding by the government to the researches.

Machine Learning from theory to reality

- **1959:** In 1959, the first neural network was applied to a real-world problem to remove echoes over phone lines using an adaptive filter.
- **1985:** In 1985, Terry Sejnowski and Charles Rosenberg invented a neural network **NETtalk**, which was able to teach itself how to correctly pronounce 20,000 words in one week.
- **1997:** The IBM's **Deep blue** intelligent computer won the chess game against the chess expert Garry Kasparov, and it became the first computer which had beaten a human chess expert.

Machine Learning at 21st century

- **2006:** In the year 2006, computer scientist Geoffrey Hinton has given a new name to neural net research as "**deep learning**," and nowadays, it has become one of the most trending technologies.
- **2012:** In 2012, Google created a deep neural network which learned to recognize the image of humans and cats in YouTube videos.
- **2014:** In 2014, the Chabot "**Eugen Goostman**" cleared the Turing Test. It was the first Chabot who convinced the 33% of human judges that it was not a machine.
- **2014: DeepFace** was a deep neural network created by Facebook, and they claimed that it could recognize a person with the same precision as a human can do.
- **2016: AlphaGo** beat the world's number second player **Lee sedol** at **Go game**. In 2017 it beat the number one player of this game **Ke Jie**.
- **2017:** In 2017, the Alphabet's Jigsaw team built an intelligent system that was able to learn the **online trolling**. It used to read millions of comments of different websites to learn to stop online trolling.

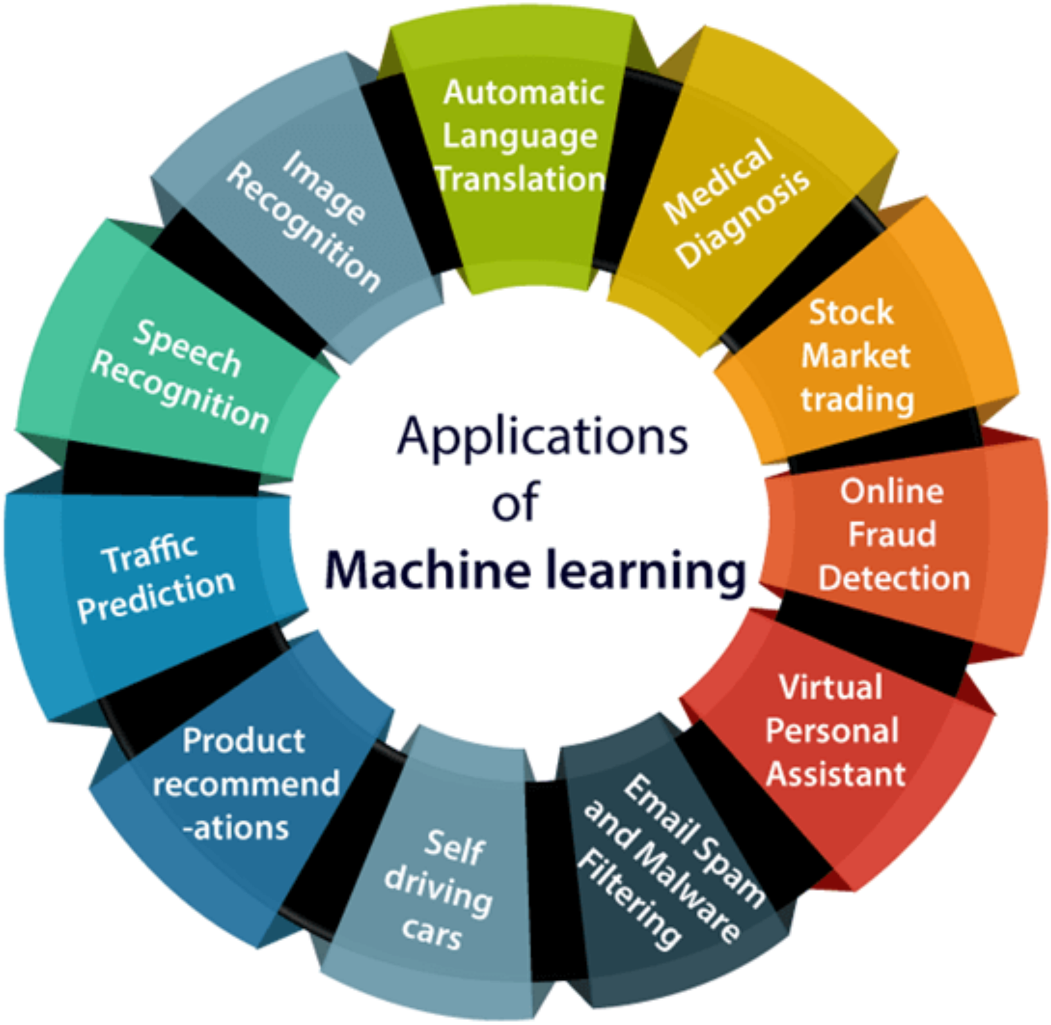
Machine Learning at present:

Now machine learning has got a great advancement in its research, and it is present everywhere around us, such as self-driving cars, Amazon Alexa, Catboats, recommender system, and many more. It includes Supervised, unsupervised, and reinforcement learning with clustering, classification, decision tree, SVM algorithms, etc.

Modern machine learning models can be used for making various predictions, including weather prediction, disease prediction, stock market analysis, etc.

Applications of Machine learning

Machine learning is a buzzword for today's technology, and it is growing very rapidly day by day. We are using machine learning in our daily life even without knowing it such as Google Maps, Google assistant, Alexa, etc. Below are some most trending real-world applications of Machine Learning:



1. Image Recognition:

Image recognition is one of the most common applications of machine learning. It is used to identify objects, persons, places, digital images, etc. The popular use case of image recognition and face detection is, **Automatic friend tagging suggestion**:

Facebook provides us a feature of auto friend tagging suggestion. Whenever we upload a photo with our Facebook friends, then we automatically get a tagging suggestion with name, and the technology behind this is machine learning's **face detection** and **recognition algorithm**.

It is based on the Facebook project named "**Deep Face**," which is responsible for face recognition and person identification in the picture.

2. Speech Recognition

While using Google, we get an option of "**Search by voice**," it comes under speech recognition, and it's a popular application of machine learning.

Speech recognition is a process of converting voice instructions into text, and it is also known as "**Speech to text**", or "**Computer speech recognition**." At present, machine learning algorithms are widely used by various applications of speech recognition. **Google assistant**, **Siri**, **Cortana**, and **Alexa** are using speech recognition technology to follow the voice instructions.

3. Traffic prediction:

If we want to visit a new place, we take help of Google Maps, which shows us the correct path with the shortest route and predicts the traffic conditions.

It predicts the traffic conditions such as whether traffic is cleared, slow-moving, or heavily congested with the help of two ways:

- **Real Time location** of the vehicle form Google Map app and sensors
- **Average time has taken** on past days at the same time.

Everyone who is using Google Map is helping this app to make it better. It takes information from the user and sends back to its database to improve the performance.

4. Product recommendations:

Machine learning is widely used by various e-commerce and entertainment companies such as **Amazon**, **Netflix**, etc., for product recommendation to the user. Whenever we search for some product on Amazon, then we started getting an advertisement for the same product while internet surfing on the same browser and this is because of machine learning.

Google understands the user interest using various machine learning algorithms and suggests the product as per customer interest.

As similar, when we use Netflix, we find some recommendations for entertainment series, movies, etc., and this is also done with the help of machine learning.

5. Self-driving cars:

One of the most exciting applications of machine learning is self-driving cars. Machine learning plays a significant role in self-driving cars. Tesla, the most popular car manufacturing company is working on self-driving car. It is using unsupervised learning method to train the car models to detect people and objects while driving.

6. Email Spam and Malware Filtering:

Whenever we receive a new email, it is filtered automatically as important, normal, and spam. We always receive an important mail in our inbox with the important symbol and spam emails in our spam box, and the technology behind this is Machine learning. Below are some spam filters used by Gmail:

- Content Filter
- Header filter
- General blacklists filter
- Rules-based filters
- Permission filters

Some machine learning algorithms such as **Multi-Layer Perceptron**, **Decision tree**, and **Naïve Bayes classifier** are used for email spam filtering and malware detection.

7. Virtual Personal Assistant:

We have various virtual personal assistants such as **Google assistant**, **Alexa**, **Cortana**, **Siri**. As the name suggests, they help us in finding the information using our voice instruction. These assistants can help us in various ways just by our voice instructions such as Play music, call someone, Open an email, Scheduling an appointment, etc.

These virtual assistants use machine learning algorithms as an important part.

These assistant record our voice instructions, send it over the server on a cloud, and decode it using ML algorithms and act accordingly.

8. Online Fraud Detection:

Machine learning is making our online transaction safe and secure by detecting fraud transaction. Whenever we perform some online transaction, there may be various ways that a fraudulent transaction can take place such as **fake accounts**, **fake ids**, and **steal money** in the middle of a transaction. So to detect this, **Feed Forward Neural network** helps us by checking whether it is a genuine transaction or a fraud transaction.

For each genuine transaction, the output is converted into some hash values, and these values become the input for the next round. For each genuine transaction, there is a specific pattern which gets change for the fraud transaction hence, it detects it and makes our online transactions more secure.

9. Stock Market trading:

Machine learning is widely used in stock market trading. In the stock market, there is always a risk of up and downs in shares, so for this machine learning's **long short term memory neural network** is used for the prediction of stock market trends.

10. Medical Diagnosis:

In medical science, machine learning is used for diseases diagnoses. With this, medical technology is growing very fast and able to build 3D models that can predict the exact position of lesions in the brain.

It helps in finding brain tumors and other brain-related diseases easily.

11. Automatic Language Translation:

Nowadays, if we visit a new place and we are not aware of the language then it is not a problem at all, as for this also machine learning helps us by converting the text into our known languages. Google's GNMT (Google Neural Machine Translation) provide this feature, which is a Neural Machine Learning that translates the text into our familiar language, and it called as automatic translation.

The technology behind the automatic translation is a sequence to sequence learning algorithm, which is used with image recognition and translates the text from one language to another language.

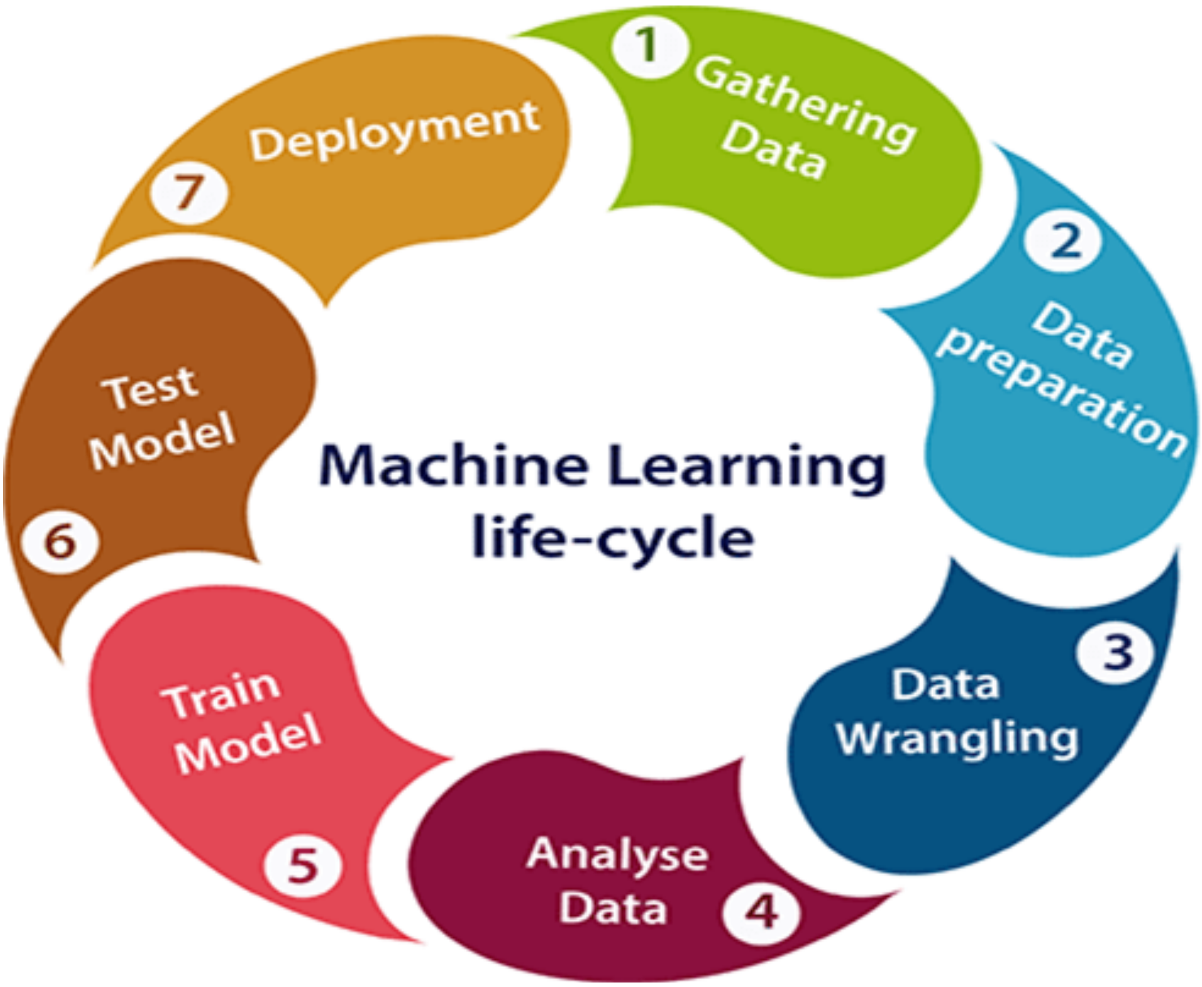
Machine learning Life cycle

Machine learning has given the computer systems the abilities to automatically learn without being explicitly programmed. But how does a machine learning system work? So, it can be described using the life cycle of machine learning. Machine learning life cycle is a cyclic process to build an efficient machine learning project. The main purpose of the life cycle is to find a solution to the problem or project.

Machine learning life cycle involves seven major steps, which are given below:

- **Gathering Data**
- **Data preparation**
- **Data Wrangling**
- **Analyse Data**

- **Train the model**
- **Test the model**
- **Deployment**



The most important thing in the complete process is to understand the problem and to know the purpose of the problem. Therefore, before starting the life cycle, we need to understand the problem because the good result depends on the better understanding of the problem.

In the complete life cycle process, to solve a problem, we create a machine learning system called "model", and this model is created by providing "training". But to train a model, we need data, hence, life cycle starts by collecting data.

1. Gathering Data:

Data Gathering is the first step of the machine learning life cycle. The goal of this step is to identify and obtain all data-related problems.

In this step, we need to identify the different data sources, as data can be collected from various sources such as **files**, **database**, **internet**, or **mobile devices**. It is one of the most important steps of the life cycle. The quantity and quality of the collected data will determine the efficiency of the output. The more will be the data, the more accurate will be the prediction.

This step includes the below tasks:

- **Identify various data sources**
- **Collect data**
- **Integrate the data obtained from different sources**

By performing the above task, we get a coherent set of data, also called as a **dataset**. It will be used in further steps.

2. Data preparation

After collecting the data, we need to prepare it for further steps. Data preparation is a step where we put our data into a suitable place and prepare it to use in our machine learning training.

In this step, first, we put all data together, and then randomize the ordering of data.

This step can be further divided into two processes:

- **Data exploration:**
  It is used to understand the nature of data that we have to work with. We need to understand the characteristics, format, and quality of data.
  A better understanding of data leads to an effective outcome. In this, we find Correlations, general trends, and outliers.
- **Data pre-processing:**
  Now the next step is preprocessing of data for its analysis.

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3. Data Wrangling

Data wrangling is the process of cleaning and converting raw data into a useable format. It is the process of cleaning the data, selecting the variable to use, and transforming the data in a proper format to make it more suitable for analysis in the next step. It is one of the most important steps of the complete process. Cleaning of data is required to address the quality issues.

It is not necessary that data we have collected is always of our use as some of the data may not be useful. In real-world applications, collected data may have various issues, including:

- **Missing Values**
- **Duplicate data**
- **Invalid data**
- **Noise**

So, we use various filtering techniques to clean the data.

It is mandatory to detect and remove the above issues because it can negatively affect the quality of the outcome.

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4. Data Analysis

Now the cleaned and prepared data is passed on to the analysis step. This step involves:

- **Selection of analytical techniques**
- **Building models**
- **Review the result**

The aim of this step is to build a machine learning model to analyze the data using various analytical techniques and review the outcome. It starts with the determination of the type of the problems, where we select the machine learning techniques such as **Classification**, **Regression**, **Cluster analysis**, **Association**, etc. then build the model using prepared data, and evaluate the model.

Hence, in this step, we take the data and use machine learning algorithms to build the model.

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5. Train Model

Now the next step is to train the model, in this step we train our model to improve its performance for better outcome of the problem.

We use datasets to train the model using various machine learning algorithms. Training a model is required so that it can understand the various patterns, rules, and, features.

6. Test Model

Once our machine learning model has been trained on a given dataset, then we test the model. In this step, we check for the accuracy of our model by providing a test dataset to it.

Testing the model determines the percentage accuracy of the model as per the requirement of project or problem.

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7. Deployment

The last step of machine learning life cycle is deployment, where we deploy the model in the real-world system.

If the above-prepared model is producing an accurate result as per our requirement with acceptable speed, then we deploy the model in the real system. But before deploying the project, we will check whether it is improving its performance using available data or not. The deployment phase is similar to making the final report for a project.

Difference between Artificial intelligence and Machine learning

Artificial intelligence and machine learning are the part of computer science that are correlated with each other. These two technologies are the most trending technologies which are used for creating intelligent systems.

Although these are two related technologies and sometimes people use them as a synonym for each other, but still both are the two different terms in various cases.

On a broad level, we can differentiate both AI and ML as:

“AI is a bigger concept to create intelligent machines that can simulate human thinking capability and behavior, whereas, machine learning is an application or subset of AI that allows machines to learn from data without being programmed explicitly.
”

Below are some main differences between AI and machine learning along with the overview of Artificial intelligence and machine learning.

Artificial Intelligence

Artificial intelligence is a field of computer science which makes a computer system that can mimic human intelligence. It is comprised of two words "**Artificial**" and "**intelligence**", which means "a human-made thinking power." Hence we can define it as,

Artificial intelligence is a technology using which we can create intelligent systems that can simulate human intelligence.

The Artificial intelligence system does not require to be pre-programmed, instead of that, they use such algorithms which can work with their own intelligence. It involves machine learning algorithms such as Reinforcement learning algorithm and deep learning neural networks. AI is being used in multiple places such as Siri, Google?s AlphaGo, AI in Chess playing, etc.

Based on capabilities, AI can be classified into three types:

- **Weak AI**
- **General AI**
- **Strong AI**

Currently, we are working with weak AI and general AI. The future of AI is Strong AI for which it is said that it will be intelligent than humans.

Machine learning

Machine learning is about extracting knowledge from the data. It can be defined as,

Machine learning is a subfield of artificial intelligence, which enables machines to learn from past data or experiences without being explicitly programmed.

Machine learning enables a computer system to make predictions or take some decisions using historical data without being explicitly programmed. Machine learning uses a massive amount of structured and semi-structured data so that a machine learning model can generate accurate result or give predictions based on that data.

Machine learning works on algorithm which learn by it?s own using historical data. It works only for specific domains such as if we are creating a machine learning model to detect pictures of dogs, it will only give result for dog images, but if we provide a new data like cat image then it will become unresponsive. Machine learning is being used in various places such as for online recommender system, for Google search algorithms, Email spam filter, Facebook Auto friend tagging suggestion, etc.

It can be divided into three types:

- **Supervised learning**
- **Reinforcement learning**
- **Unsupervised learning**

Key differences between Artificial Intelligence (AI) and Machine learning (ML):

Artificial Intelligence	**Machine learning**
Artificial intelligence is a technology which enables a machine to simulate human behavior.	Machine learning is a subset of AI which allows a machine to automatically learn from past data without programming explicitly.
The goal of AI is to make a smart computer system like humans to solve complex problems.	The goal of ML is to allow machines to learn from data so that they can give accurate output.

In AI, we make intelligent systems to perform any task like a human.	In ML, we teach machines with data to perform a particular task and give an accurate result.
Machine learning and deep learning are the two main subsets of AI.	Deep learning is a main subset of machine learning.
AI has a very wide range of scope.	Machine learning has a limited scope.
AI is working to create an intelligent system which can perform various complex tasks.	Machine learning is working to create machines that can perform only those specific tasks for which they are trained.
AI system is concerned about maximizing the chances of success.	Machine learning is mainly concerned about accuracy and patterns.
The main applications of AI are **Siri, customer support using catboats**, Expert System, Online game playing, intelligent humanoid robot, etc.	The main applications of machine learning are **Online recommender system**, **Google search algorithms**, **Facebook auto friend tagging suggestions**, etc.
On the basis of capabilities, AI can be divided into three types, which are, **Weak AI**, **General AI**, and **Strong AI**.	Machine learning can also be divided into mainly three types that are **Supervised learning**, **Unsupervised learning**, and **Reinforcement learning**.
It includes learning, reasoning, and self-correction.	It includes learning and self-correction when introduced with new data.
AI completely deals with Structured, semi-structured, and unstructured data.	Machine learning deals with Structured and semi-structured data.

How to get datasets for Machine Learning

The key to success in the field of machine learning or to become a great data scientist is to practice with different types of datasets. But discovering a suitable dataset for each kind of machine learning project is a difficult task. So, in this topic, we will provide the detail of the sources from where you can easily get the dataset according to your project.

Before knowing the sources of the machine learning dataset, let's discuss datasets.

What is a dataset?

A dataset is a collection of data in which data is arranged in some order. A dataset can contain any data from a series of an array to a database table. Below table shows an example of the dataset:

Country	Age	Salary	Purchased
India	38	48000	No
France	43	45000	Yes
Germany	30	54000	No
France	48	65000	No
Germany	40		Yes
India	35	58000	Yes

A tabular dataset can be understood as a database table or matrix, where each column corresponds to a **particular variable,** and each row corresponds to the **fields of the dataset.** The most supported file type for a tabular dataset is **"Comma Separated File,"** or **CSV.** But to store a "tree-like data," we can use the JSON file more efficiently.

Types of data in datasets

- **Numerical data:** Such as house price, temperature, etc.
- **Categorical data:** Such as Yes/No, True/False, Blue/green, etc.
- **Ordinal data:** These data are similar to categorical data but can be measured on the basis of comparison.

Note: A real-world dataset is of huge size, which is difficult to manage and process at the initial level. Therefore, to practice machine learning algorithms, we can use any dummy dataset.

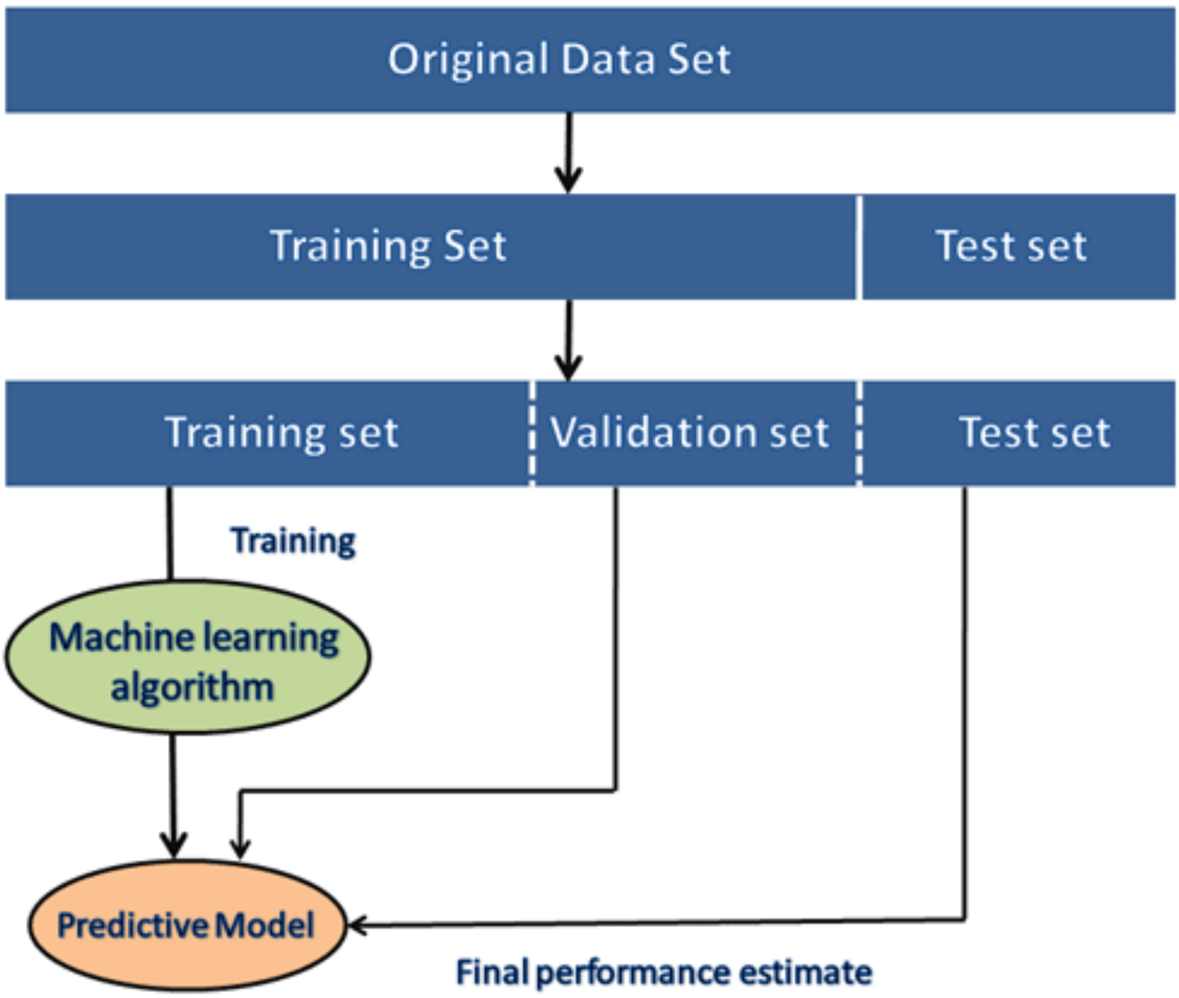
Need of Dataset

To work with machine learning projects, we need a huge amount of data, because, without the data, one cannot train ML/AI models. Collecting and preparing the dataset is one of the most crucial parts while creating an ML/AI project.

The technology applied behind any ML projects cannot work properly if the dataset is not well prepared and pre-processed.

During the development of the ML project, the developers completely rely on the datasets. In building ML applications, datasets are divided into two parts:

- **Training dataset:**
- **Test Dataset**

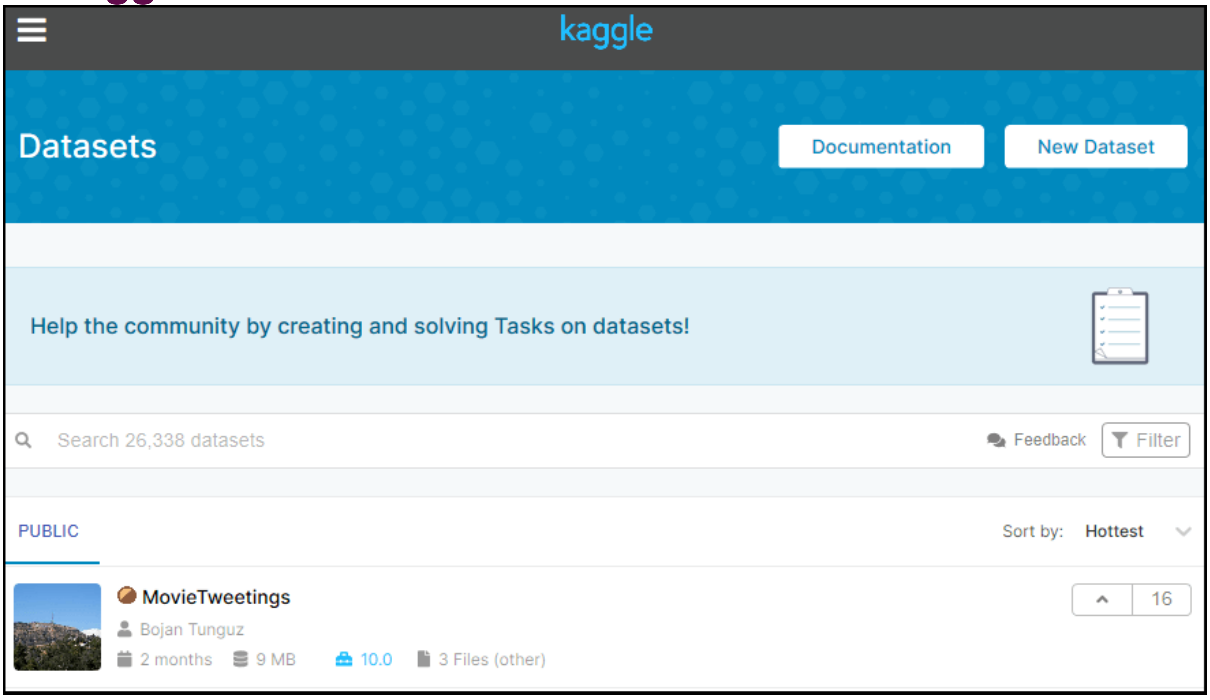


Note: The datasets are of large size, so to download these datasets, you must have fast internet on your computer.

Popular sources for Machine Learning datasets

Below is the list of datasets which are freely available for the public to work on it:

1. Kaggle Datasets



Kaggle is one of the best sources for providing datasets for Data Scientists and Machine Learners. It allows users to find, download, and publish datasets in an easy way. It also provides the opportunity to work with other machine learning engineers and solve difficult Data Science related tasks.

Kaggle provides a high-quality dataset in different formats that we can easily find and download.

The link for the Kaggle dataset is https://www.kaggle.com/datasets

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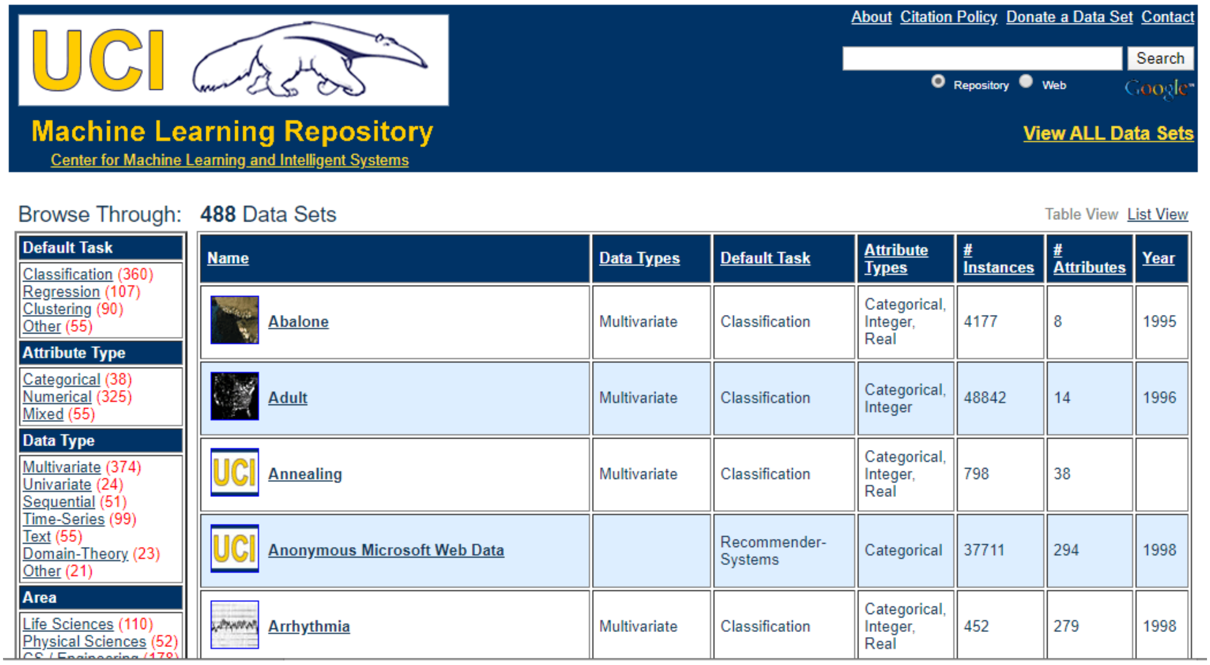
2. UCI Machine Learning Repository



UCI Machine learning repository is one of the great sources of machine learning datasets. This repository contains databases, domain theories, and data generators that are widely used by the machine learning community for the analysis of ML algorithms.

Since the year 1987, it has been widely used by students, professors, researchers as a primary source of machine learning dataset.

It classifies the datasets as per the problems and tasks of machine learning such as **Regression, Classification, Clustering, etc.** It also contains some of the popular datasets such as the **Iris dataset, Car Evaluation dataset, Poker Hand dataset, etc.**

The link for the UCI machine learning repository is https://archive.ics.uci.edu/ml/index.php

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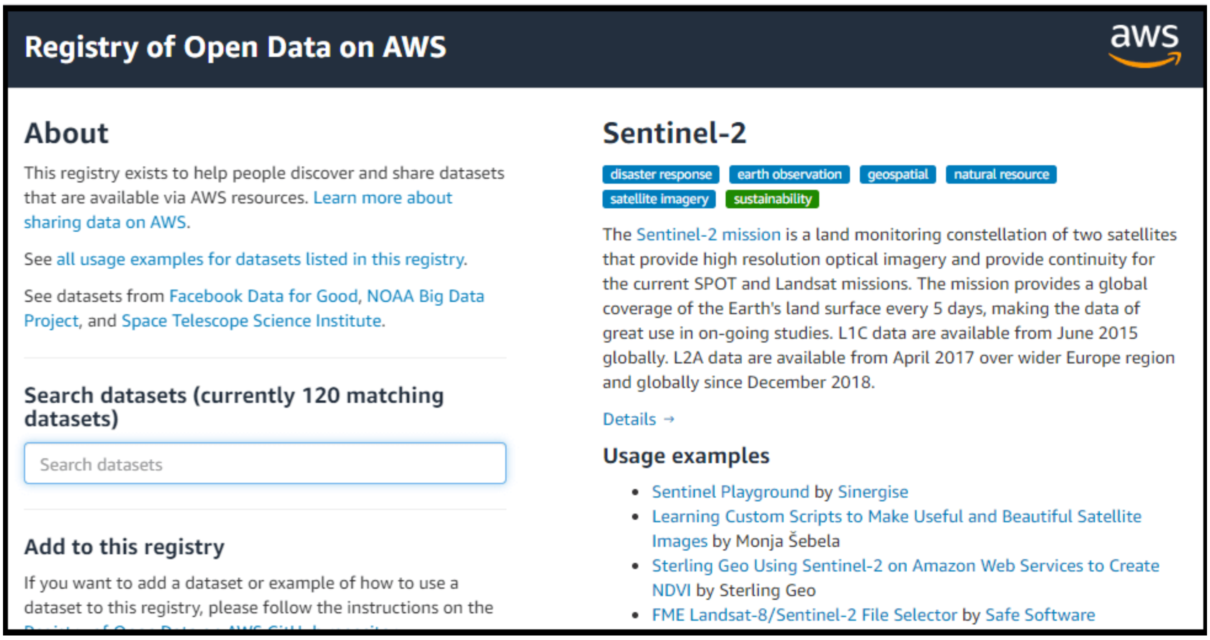
3. Datasets via AWS



We can search, download, access, and share the datasets that are publicly available via AWS resources. These datasets can be accessed through AWS resources but provided and maintained by different government organizations, researches, businesses, or individuals.

Anyone can analyze and build various services using shared data via AWS resources. The shared dataset on cloud helps users to spend more time on data analysis rather than on acquisitions of data.

This source provides the various types of datasets with examples and ways to use the dataset. It also provides the search box using which we can search for the required dataset. Anyone can add any dataset or example to the **Registry of Open Data on AWS.**

The link for the resource is https://registry.opendata.aws/

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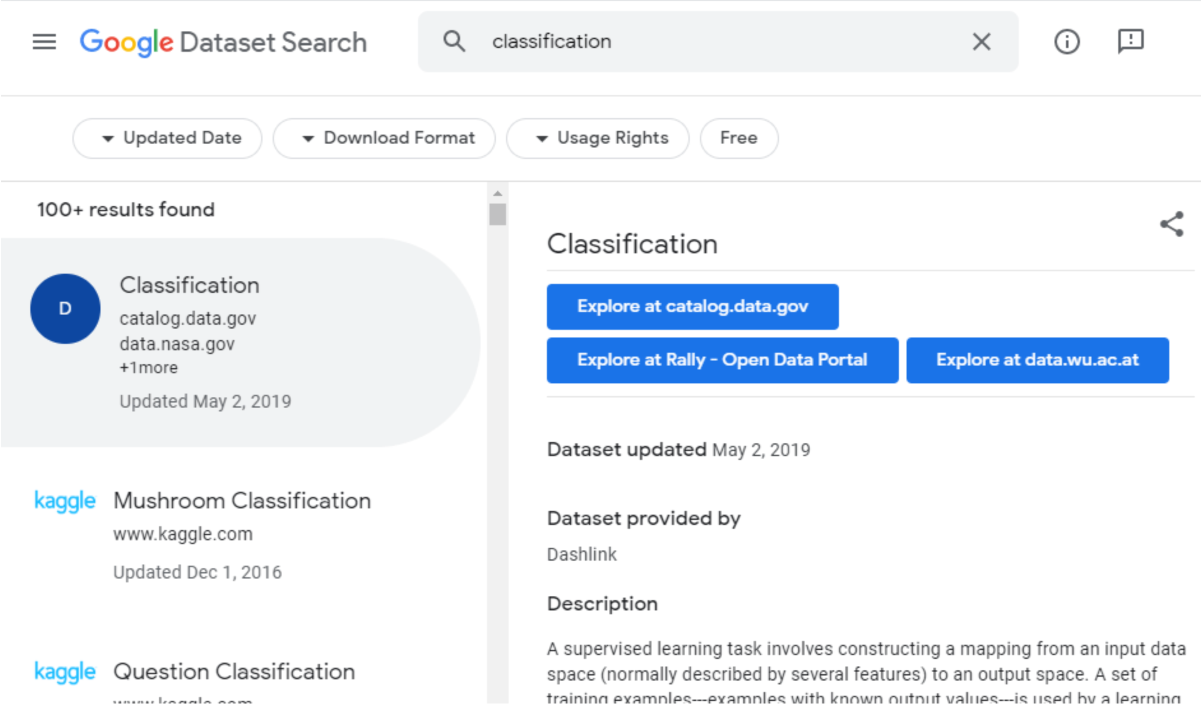
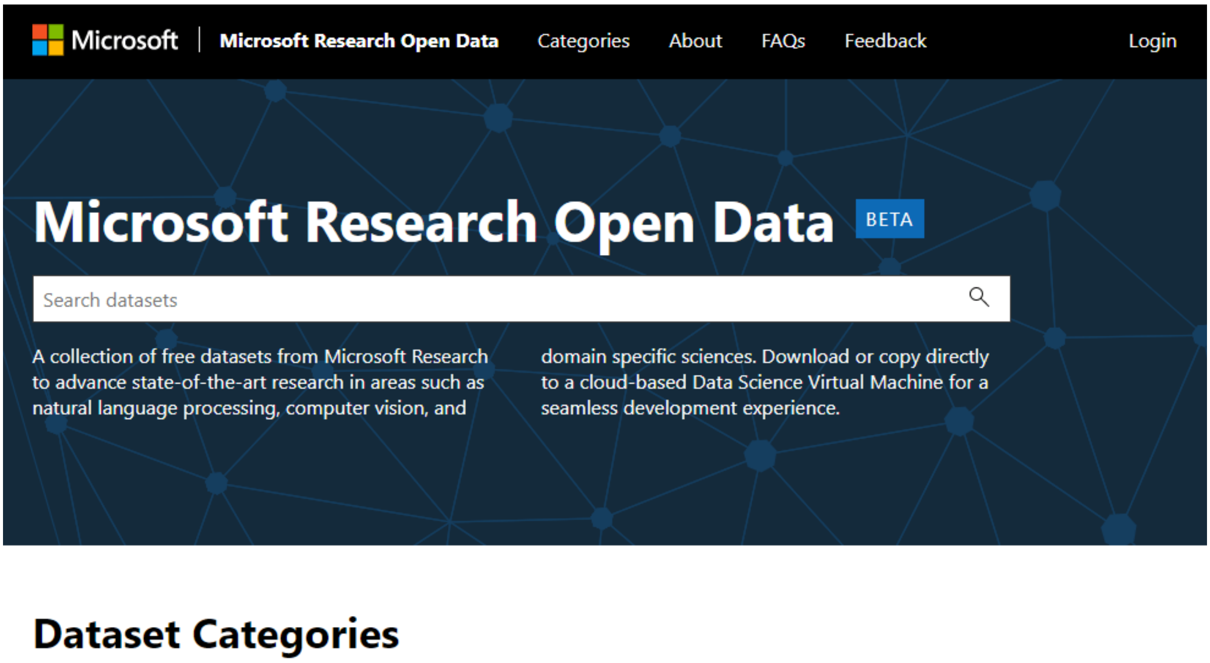
4. Google's Dataset Search Engine



Google dataset search engine is a search engine launched by **Google** on **September 5, 2018.** This source helps researchers to get online datasets that are freely available for use.

The link for the Google dataset search engine is https://toolbox.google.com/datasetsearch

5. Microsoft Datasets

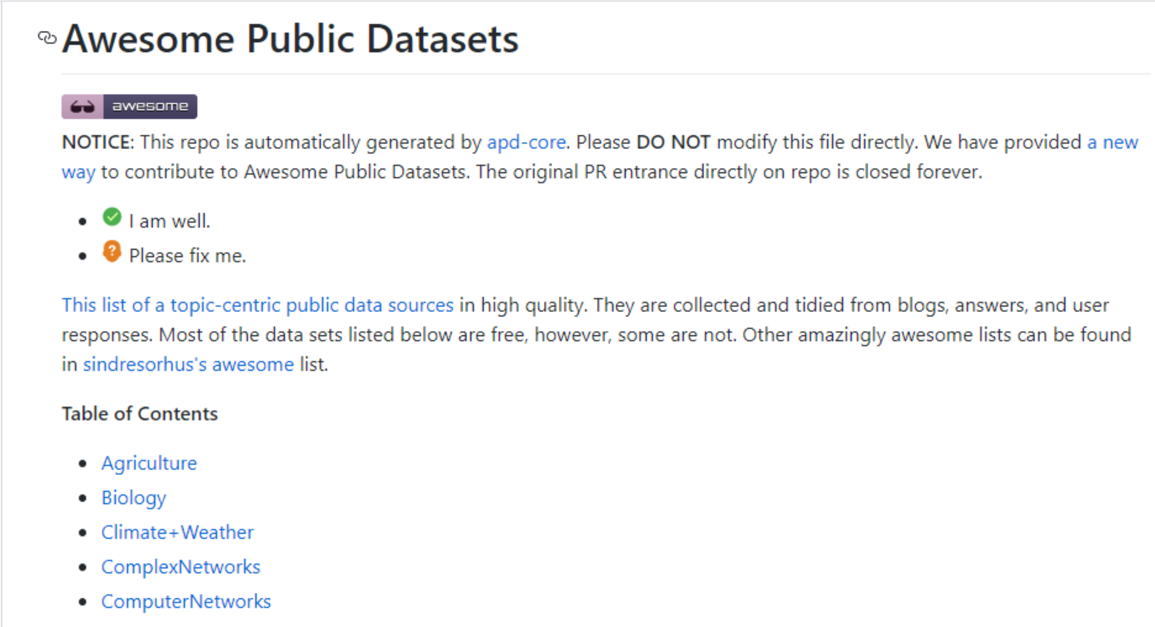


The Microsoft has launched the **"Microsoft Research Open data"** repository with the collection of free datasets in various areas such as **natural language processing, computer vision, and domain-specific sciences.**

Using this resource, we can download the datasets to use on the current device, or we can also directly use it on the cloud infrastructure.

The link to download or use the dataset from this resource is https://msropendata.com/

6. Awesome Public Dataset Collection



Awesome Public Datasets

awesome

NOTICE: This repo is automatically generated by apd-core. Please **DO NOT** modify this file directly. We have provided a new way to contribute to Awesome Public Datasets. The original PR entrance directly on repo is closed forever.

- I am well.
- Please fix me.

This list of a topic-centric public data sources in high quality. They are collected and tidied from blogs, answers, and user responses. Most of the data sets listed below are free, however, some are not. Other amazingly awesome lists can be found in sindresorhus's awesome list.

Table of Contents

- Agriculture
- Biology
- Climate+Weather
- ComplexNetworks
- ComputerNetworks

Awesome public dataset collection provides high-quality datasets that are arranged in a well-organized manner within a list according to topics such as Agriculture, Biology, Climate, Complex networks, etc. Most of the datasets are available free, but some may not, so it is better to check the license before downloading the dataset.

The link to download the dataset from Awesome public dataset collection is https://github.com/awesomedata/awesome-public-datasets

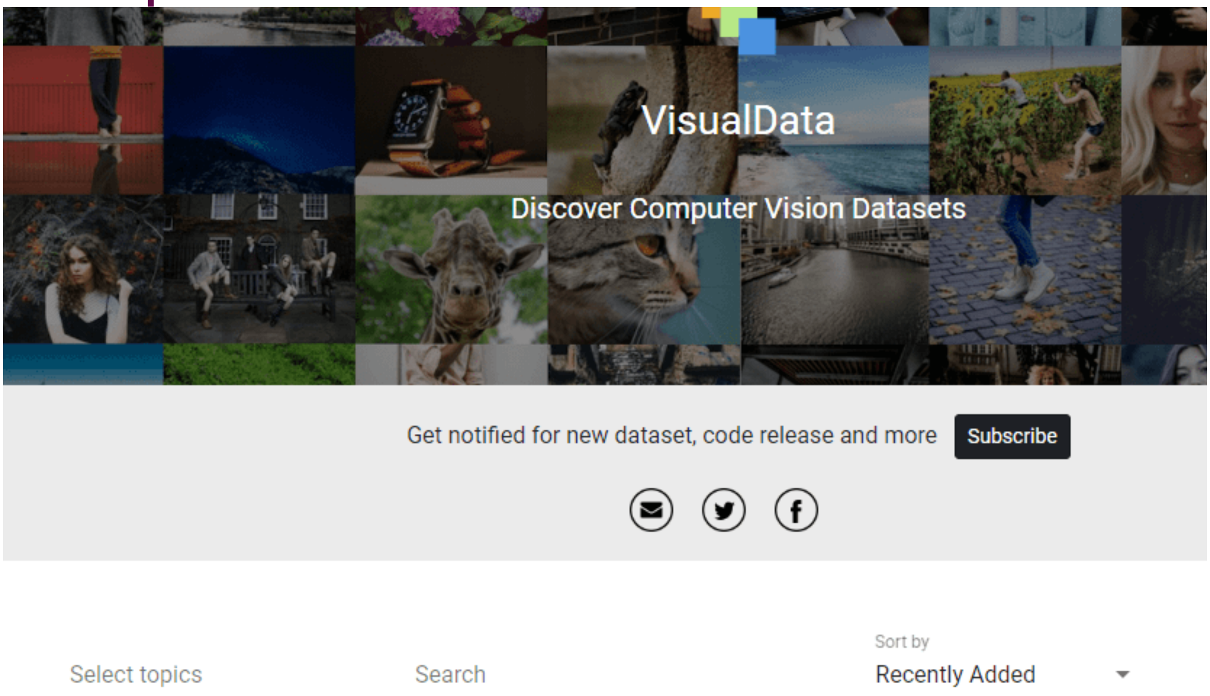
7. Government Datasets

There are different sources to get government-related data. Various countries publish government data for public use collected by them from different departments.

The goal of providing these datasets is to increase transparency of government work among the people and to use the data in an innovative approach. Below are some links of government datasets:

- Indian Government dataset
- US Government Dataset
- Northern Ireland Public Sector Datasets
- European Union Open Data Portal

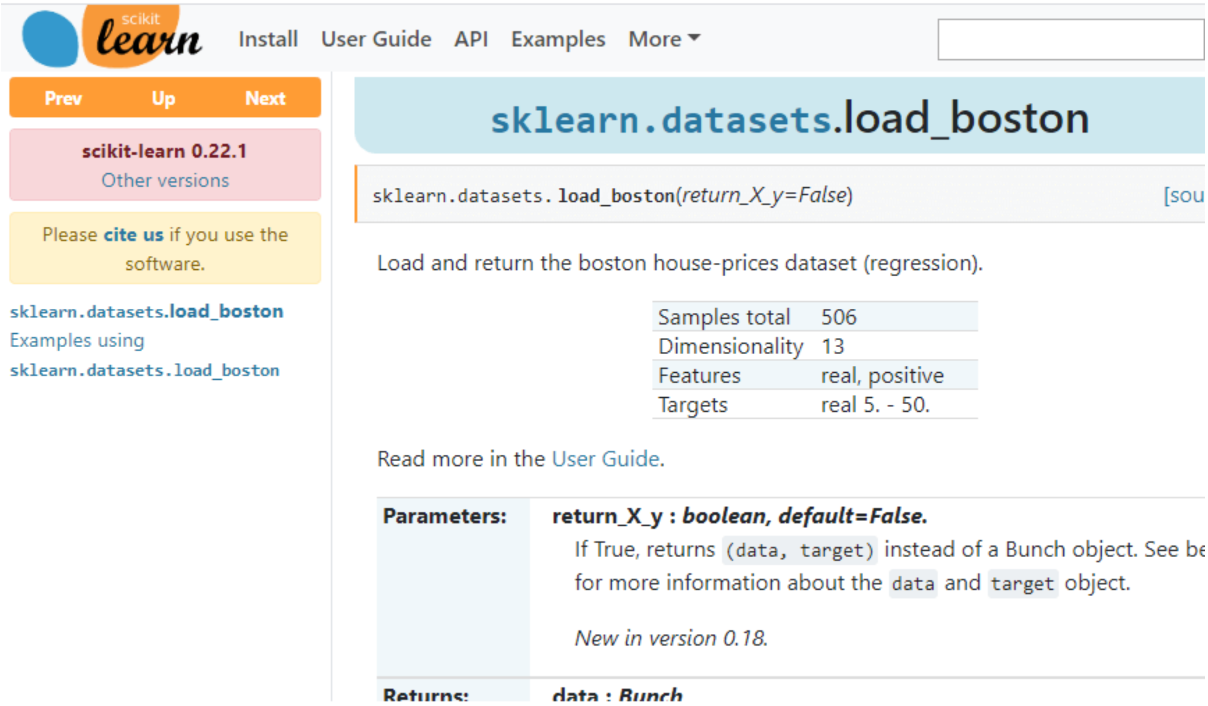
8. Computer Vision Datasets



Visual data provides multiple numbers of the great dataset that are specific to computer visions such as Image Classification, Video classification, Image Segmentation, etc. Therefore, if you want to build a project on deep learning or image processing, then you can refer to this source.

The link for downloading the dataset from this source is https://www.visualdata.io/

9. Scikit-learn dataset



Scikit-learn is a great source for machine learning enthusiasts. This source provides both toy and real-world datasets. These datasets can be obtained from sklearn.datasets package and using general dataset API.

The toy dataset available on scikit-learn can be loaded using some predefined functions such as, **load_boston([return_X_y]), load_iris([return_X_y]),** etc, rather than importing any file from external sources. But these datasets are not suitable for real-world projects.

The link to download datasets from this source is https://scikit-learn.org/stable/datasets/index.html

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Data Preprocessing in Machine learning

Data preprocessing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model.

When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So for this, we use data preprocessing task.

Why do we need Data Preprocessing?

A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data preprocessing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

It involves below steps:

- **Getting the dataset**
- **Importing libraries**
- **Importing datasets**
- **Finding Missing Data**
- **Encoding Categorical Data**
- **Splitting dataset into training and test set**
- **Feature scaling**

---

1) Get the Dataset

To create a machine learning model, the first thing we required is a dataset as a machine learning model completely works on data. The collected data for a particular problem in a proper format is known as the **dataset**.

Dataset may be of different formats for different purposes, such as, if we want to create a machine learning model for business purpose, then dataset will be different with the dataset required for a liver patient. So each dataset is different from another dataset. To use the dataset in our code, we usually put it into a CSV **file**. However, sometimes, we may also need to use an HTML or xlsx file.

What is a CSV File?

CSV stands for "**Comma-Separated Values**" files; it is a file format which allows us to save the tabular data, such as spreadsheets. It is useful for huge datasets and can use these datasets in programs.

Here we will use a demo dataset for data preprocessing, and for practice, it can be downloaded from here, "https://www.superdatascience.com/pages/machine-learning

. For real-world problems, we can download datasets online from various sources such as https://www.kaggle.com/uciml/datasets
, https://archive.ics.uci.edu/ml/index.php
etc.

We can also create our dataset by gathering data using various API with Python and put that data into a .csv file.

2) Importing Libraries

In order to perform data preprocessing using Python, we need to import some predefined Python libraries. These libraries are used to perform some specific jobs. There are three specific libraries that we will use for data preprocessing, which are:

Numpy: Numpy Python library is used for including any type of mathematical operation in the code. It is the fundamental package for scientific calculation in Python. It also supports to add large, multidimensional arrays and matrices. So, in Python, we can import it as:

```
import numpy as nm
```

Here we have used **nm**, which is a short name for Numpy, and it will be used in the whole program.

Matplotlib: The second library is **matplotlib**, which is a Python 2D plotting library, and with this library, we need to import a sub-library **pyplot**. This library is used to plot any type of charts in Python for the code. It will be imported as below:

1. import matplotlib.pyplot as mpt

Here we have used mpt as a short name for this library.

Pandas: The last library is the Pandas library, which is one of the most famous Python libraries and used for importing and managing the datasets. It is an open-source data manipulation and analysis library. It will be imported as below:

Here, we have used pd as a short name for this library. Consider the below image:

```
# importing libraries
import numpy as nm
import matplotlib.pyplot as mtp
import pandas as pd

```

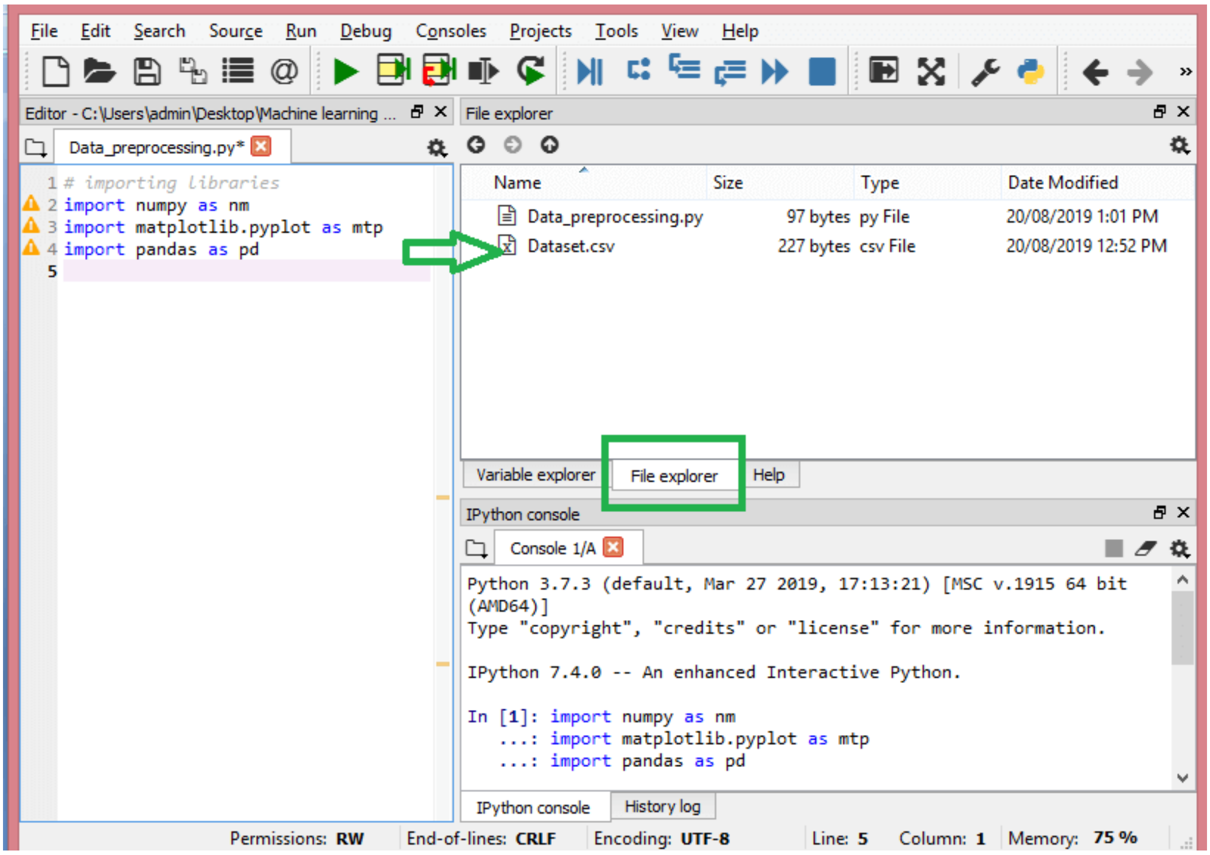
3) Importing the Datasets

Now we need to import the datasets which we have collected for our machine learning project. But before importing a dataset, we need to set the current directory as a working directory. To set a working directory in Spyder IDE, we need to follow the below steps:

1. Save your Python file in the directory which contains dataset.
2. Go to File explorer option in Spyder IDE, and select the required directory.
3. Click on F5 button or run option to execute the file.

> *Note:* ***We can set any directory as a working directory, but it must contain the required dataset.***

Here, in the below image, we can see the Python file along with required dataset. Now, the current folder is set as a working directory.



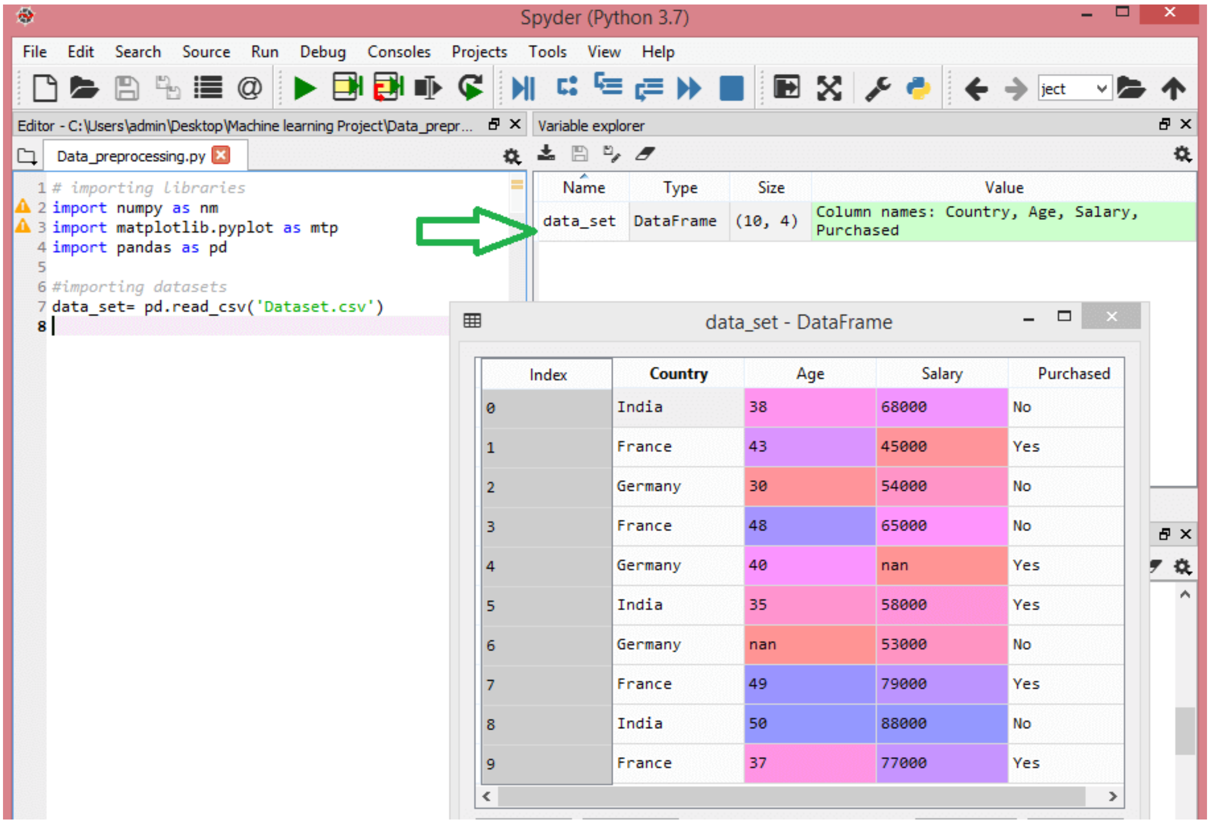
read_csv() function:

Now to import the dataset, we will use read_csv() function of pandas library, which is used to read a csv file and performs various operations on it. Using this function, we can read a csv file locally as well as through an URL.

We can use read_csv function as below:

1. data_set= pd.read_csv('Dataset.csv')

Here, **data_set** is a name of the variable to store our dataset, and inside the function, we have passed the name of our dataset. Once we execute the above line of code, it will successfully import the dataset in our code. We can also check the imported dataset by clicking on the section **variable explorer**, and then double click on **data_set**. Consider the below image:



As in the above image, indexing is started from 0, which is the default indexing in Python. We can also change the format of our dataset by clicking on the format option.

Extracting dependent and independent variables:

In machine learning, it is important to distinguish the matrix of features (independent variables) and dependent variables from dataset. In our dataset, there are three independent variables that are **Country, Age**, and **Salary**, and one is a dependent variable which is **Purchased**.

Extracting independent variable:

To extract an independent variable, we will use **iloc[ ]** method of Pandas library. It is used to extract the required rows and columns from the dataset.

1. x= data_set.iloc[:,:-1].values

In the above code, the first colon(:) is used to take all the rows, and the second colon(:) is for all the columns. Here we have used :-1, because we don't want to take the last column as it contains the dependent variable. So by doing this, we will get the matrix of features.

By executing the above code, we will get output as:

1. [['India' 38.0 68000.0]
2. ['France' 43.0 45000.0]
3. ['Germany' 30.0 54000.0]
4. ['France' 48.0 65000.0]
5. ['Germany' 40.0 nan]
6. ['India' 35.0 58000.0]
7. ['Germany' nan 53000.0]
8. ['France' 49.0 79000.0]
9. ['India' 50.0 88000.0]
10. ['France' 37.0 77000.0]]

As we can see in the above output, there are only three variables.

Extracting dependent variable:

To extract dependent variables, again, we will use Pandas .iloc[] method.

1. y= data_set.iloc[:,3].values

Here we have taken all the rows with the last column only. It will give the array of dependent variables.

By executing the above code, we will get output as:

Output:

```
array(['No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes'],
      dtype=object)
```

*Note: **If you are using Python language for machine learning, then extraction is mandatory, but for R language it is not required.***

4) Handling Missing data:

The next step of data preprocessing is to handle missing data in the datasets. If our dataset contains some missing data, then it may create a huge problem for our machine learning model. Hence it is necessary to handle missing values present in the dataset.

Ways to handle missing data:

There are mainly two ways to handle missing data, which are:

By deleting the particular row: The first way is used to commonly deal with null values. In this way, we just delete the specific row or column which consists of null values. But this way is not so efficient and removing data may lead to loss of information which will not give the accurate output.

By calculating the mean: In this way, we will calculate the mean of that column or row which contains any missing value and will put it on the place of missing value. This strategy is useful for the features which have numeric data such as age, salary, year, etc. Here, we will use this approach.

To handle missing values, we will use **Scikit-learn** library in our code, which contains various libraries for building machine learning models. Here we will use **Imputer** class of **sklearn.preprocessing** library. Below is the code for it:

1. #handling missing data (Replacing missing data with the mean value)
2. from sklearn.preprocessing import Imputer
3. imputer= Imputer(missing_values ='NaN', strategy='mean', axis = 0)
4. #Fitting imputer object to the independent variables x.
5. imputerimputer= imputer.fit(x[:, 1:3])
6. #Replacing missing data with the calculated mean value
7. x[:, 1:3]= imputer.transform(x[:, 1:3])

Output:

```
array([['India', 38.0, 68000.0],
       ['France', 43.0, 45000.0],
       ['Germany', 30.0, 54000.0],
       ['France', 48.0, 65000.0],
       ['Germany', 40.0, 65222.22222222222],
       ['India', 35.0, 58000.0],
       ['Germany', 41.111111111111114, 53000.0],
       ['France', 49.0, 79000.0],
       ['India', 50.0, 88000.0],
       ['France', 37.0, 77000.0]], dtype=object
```

As we can see in the above output, the missing values have been replaced with the means of rest column values.

5) Encoding Categorical data:

Categorical data is data which has some categories such as, in our dataset; there are two categorical variable, **Country**, and **Purchased**.

Since machine learning model completely works on mathematics and numbers, but if our dataset would have a categorical variable, then it may create trouble while building the model. So it is necessary to encode these categorical variables into numbers.

For Country variable:

Firstly, we will convert the country variables into categorical data. So to do this, we will use **LabelEncoder()** class from **preprocessing** library.

1. #Catgorical data
2. #for Country Variable
3. from sklearn.preprocessing import LabelEncoder
4. label_encoder_x= LabelEncoder()
5. x[:, 0]= label_encoder_x.fit_transform(x[:, 0])

Output:

```
Out[15]:
  array([[2, 38.0, 68000.0],
             [0, 43.0, 45000.0],
         [1, 30.0, 54000.0],
         [0, 48.0, 65000.0],
         [1, 40.0, 65222.22222222222],
         [2, 35.0, 58000.0],
         [1, 41.111111111111114, 53000.0],
         [0, 49.0, 79000.0],
         [2, 50.0, 88000.0],
        [0, 37.0, 77000.0]], dtype=object)
```

Explanation:

In above code, we have imported **LabelEncoder** class of **sklearn library**. This class has successfully encoded the variables into digits.

But in our case, there are three country variables, and as we can see in the above output, these variables are encoded into 0, 1, and 2. By these values, the machine learning model may assume that there is some correlation between these variables which will produce the wrong output. So to remove this issue, we will use **dummy encoding**.

Dummy Variables:

Dummy variables are those variables which have values 0 or 1. The 1 value gives the presence of that variable in a particular column, and rest variables become 0. With dummy encoding, we will have a number of columns equal to the number of categories.

In our dataset, we have 3 categories so it will produce three columns having 0 and 1 values. For Dummy Encoding, we will use **OneHotEncoder** class of **preprocessing** library.

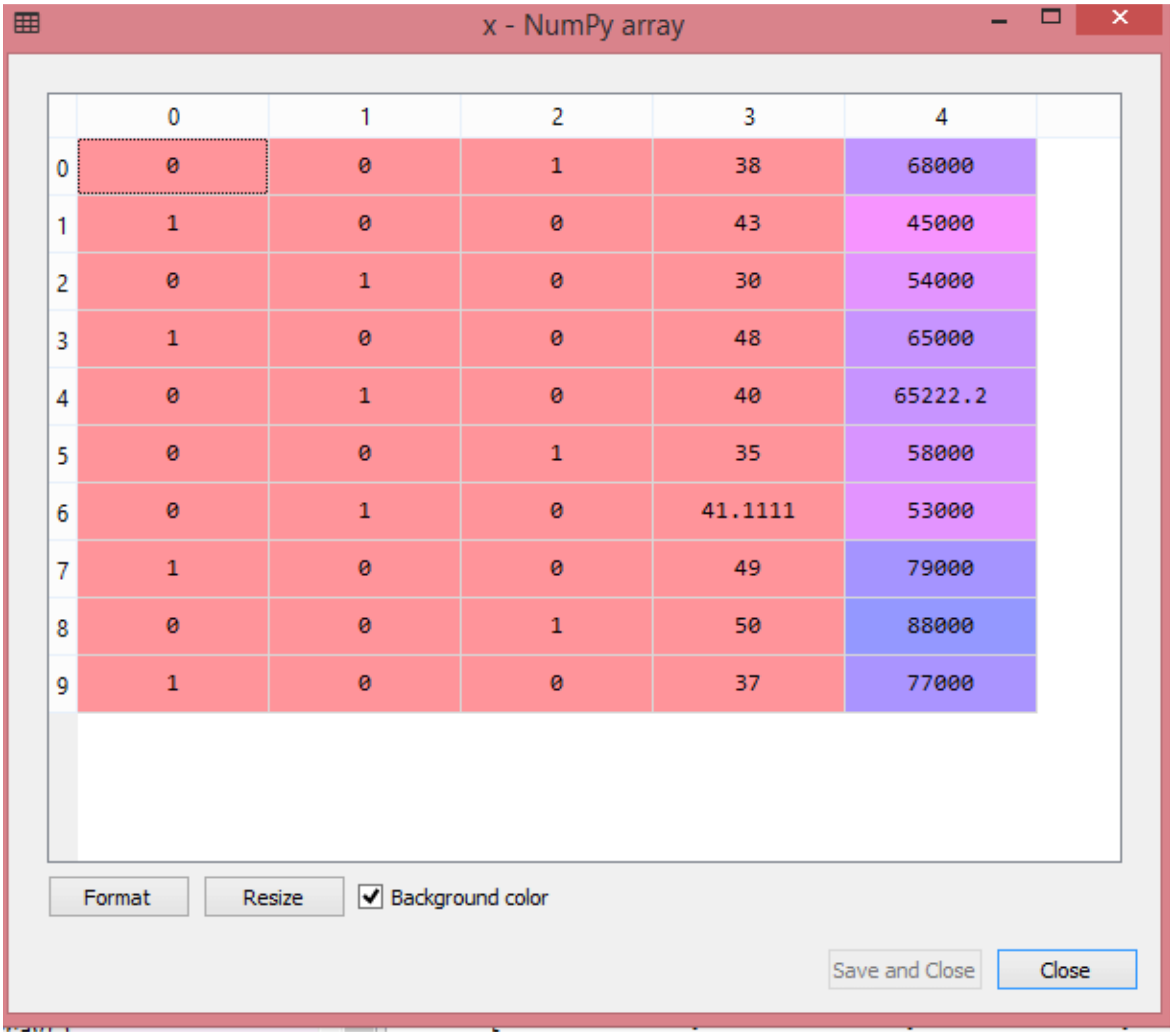
```
1. #for Country Variable
2. from sklearn.preprocessing import LabelEncoder, OneHotEncoder
3. label_encoder_x= LabelEncoder()
4. x[:, 0]= label_encoder_x.fit_transform(x[:, 0])
5. #Encoding for dummy variables
6. onehot_encoder= OneHotEncoder(categorical_features= [0])
7. x= onehot_encoder.fit_transform(x).toarray()
```

Output:

```
array([[0.00000000e+00, 0.00000000e+00, 1.00000000e+00, 3.80000000e+01,
        6.80000000e+04],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, 4.30000000e+01,
        4.50000000e+04],
       [0.00000000e+00, 1.00000000e+00, 0.00000000e+00, 3.00000000e+01,
        5.40000000e+04],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, 4.80000000e+01,
        6.50000000e+04],
       [0.00000000e+00, 1.00000000e+00, 0.00000000e+00, 4.00000000e+01,
        6.52222222e+04],
       [0.00000000e+00, 0.00000000e+00, 1.00000000e+00, 3.50000000e+01,
        5.80000000e+04],
       [0.00000000e+00, 1.00000000e+00, 0.00000000e+00, 4.11111111e+01,
        5.30000000e+04],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, 4.90000000e+01,
        7.90000000e+04],
       [0.00000000e+00, 0.00000000e+00, 1.00000000e+00, 5.00000000e+01,
        8.80000000e+04],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, 3.70000000e+01,
        7.70000000e+04]])
```

As we can see in the above output, all the variables are encoded into numbers 0 and 1 and divided into three columns.

It can be seen more clearly in the variables explorer section, by clicking on x option as:



	0	1	2	3	4
0	0	0	1	38	68000
1	1	0	0	43	45000
2	0	1	0	30	54000
3	1	0	0	48	65000
4	0	1	0	40	65222.2
5	0	0	1	35	58000
6	0	1	0	41.1111	53000
7	1	0	0	49	79000
8	0	0	1	50	88000
9	1	0	0	37	77000

For Purchased Variable:

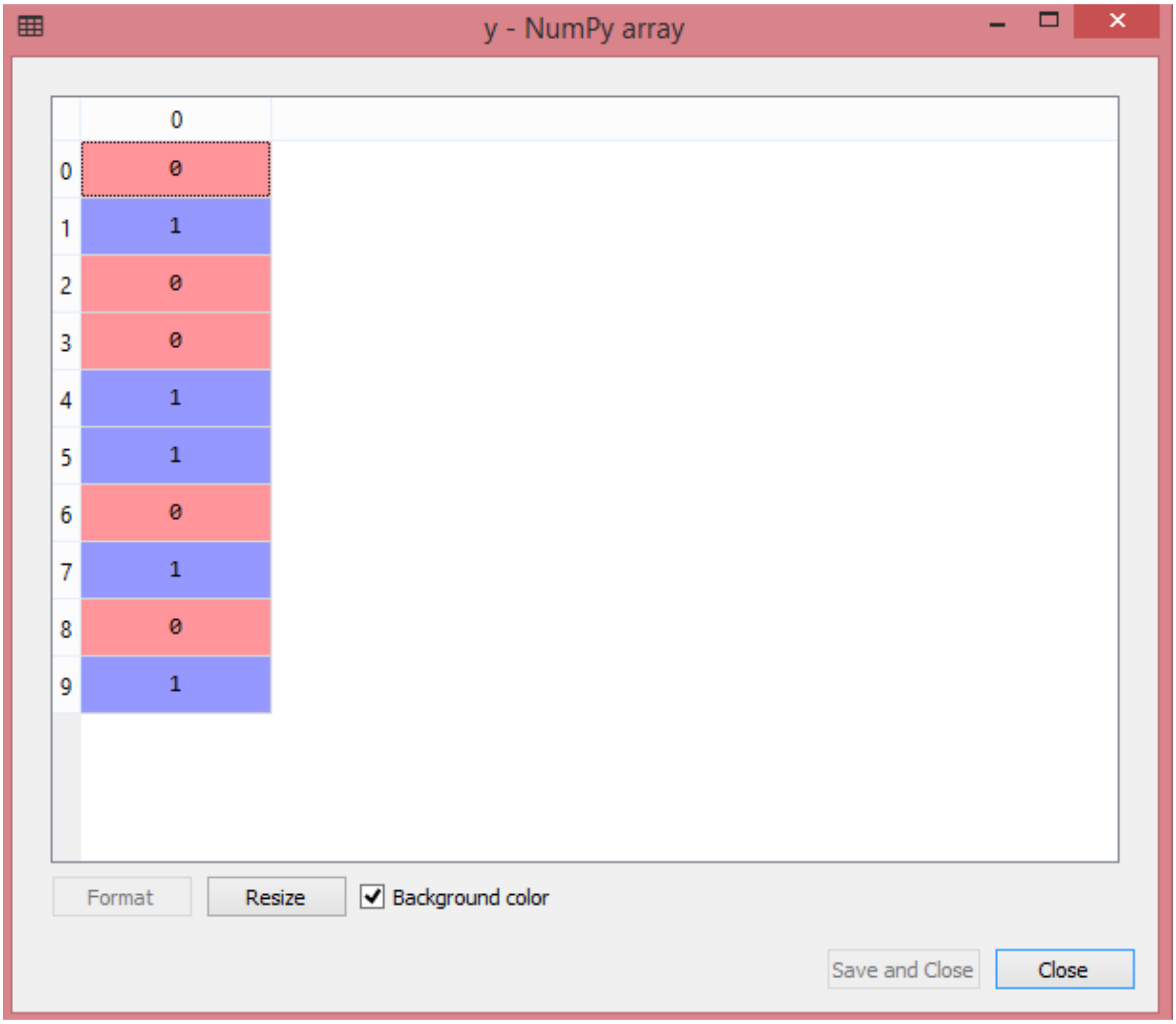
```
1. labelencoder_y= LabelEncoder()
2. y= labelencoder_y.fit_transform(y)
```

For the second categorical variable, we will only use labelencoder object of **LableEncoder** class. Here we are not using **OneHotEncoder** class because the purchased variable has only two categories yes or no, and which are automatically encoded into 0 and 1.

Output:

```
Out[17]: array([0, 1, 0, 0, 1, 1, 0, 1, 0, 1])
```

It can also be seen as:

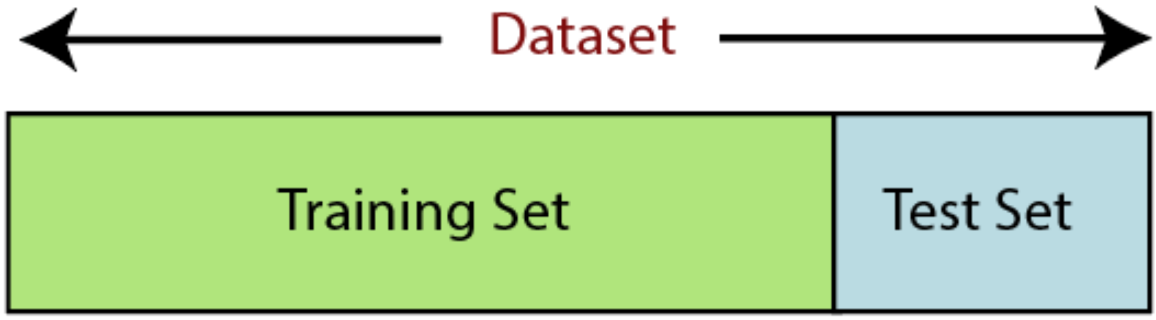


6) Splitting the Dataset into the Training set and Test set

In machine learning data preprocessing, we divide our dataset into a training set and test set. This is one of the crucial steps of data preprocessing as by doing this, we can enhance the performance of our machine learning model.

Suppose, if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models.

If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:



Training Set: A subset of dataset to train the machine learning model, and we already know the output.

Test set: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

For splitting the dataset, we will use the below lines of code:

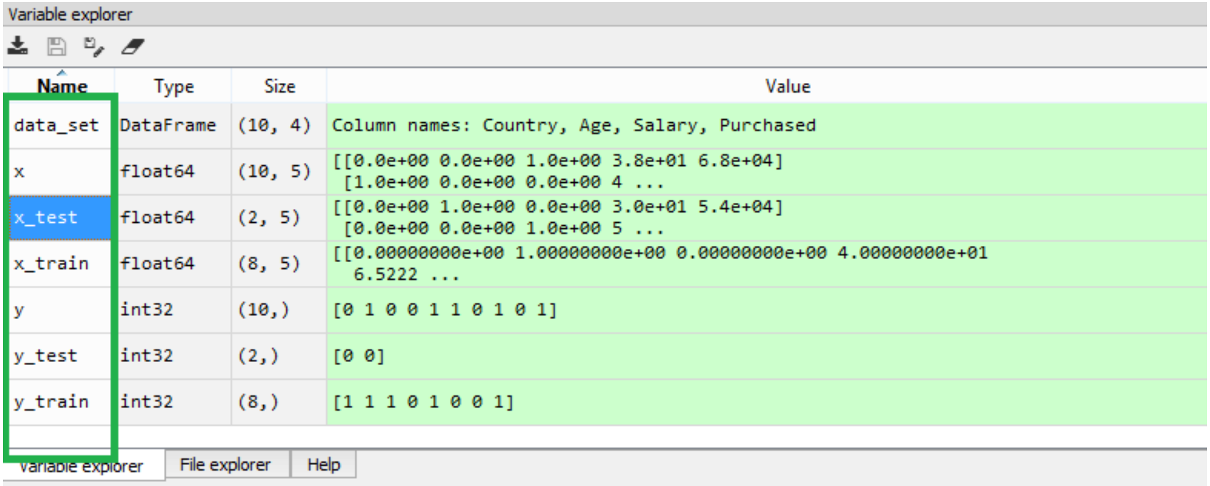
```
1. from sklearn.model_selection import train_test_split
2. x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.2, random_state
   =0)
```

Explanation:

- In the above code, the first line is used for splitting arrays of the dataset into random train and test subsets.
- In the second line, we have used four variables for our output that are
  - **x_train:** features for the training data
  - **x_test:** features for testing data
  - **y_train:** Dependent variables for training data
  - **y_test:** Independent variable for testing data
- In **train_test_split() function**, we have passed four parameters in which first two are for arrays of data, and **test_size** is for specifying the size of the test set. The test_size maybe .5, .3, or .2, which tells the dividing ratio of training and testing sets.
- The last parameter **random_state** is used to set a seed for a random generator so that you always get the same result, and the most used value for this is 42.

Output:

By executing the above code, we will get 4 different variables, which can be seen under the variable explorer section.



As we can see in the above image, the x and y variables are divided into 4 different variables with corresponding values.

7) Feature Scaling

Feature scaling is the final step of data preprocessing in machine learning. It is a technique to standardize the independent variables of the dataset in a specific range. In feature scaling, we put our variables in the same range and in the same scale so that no any variable dominate the other variable.

Consider the below dataset:

data_set - DataFrame

Index	Country	Age	Salary	Purchased
0	India	38	68000	No
1	France	43	45000	Yes
2	Germany	30	54000	No
3	France	48	65000	No
4	Germany	40	nan	Yes
5	India	35	58000	Yes
6	Germany	nan	53000	No
7	France	49	79000	Yes
8	India	50	88000	No
9	France	37	77000	Yes

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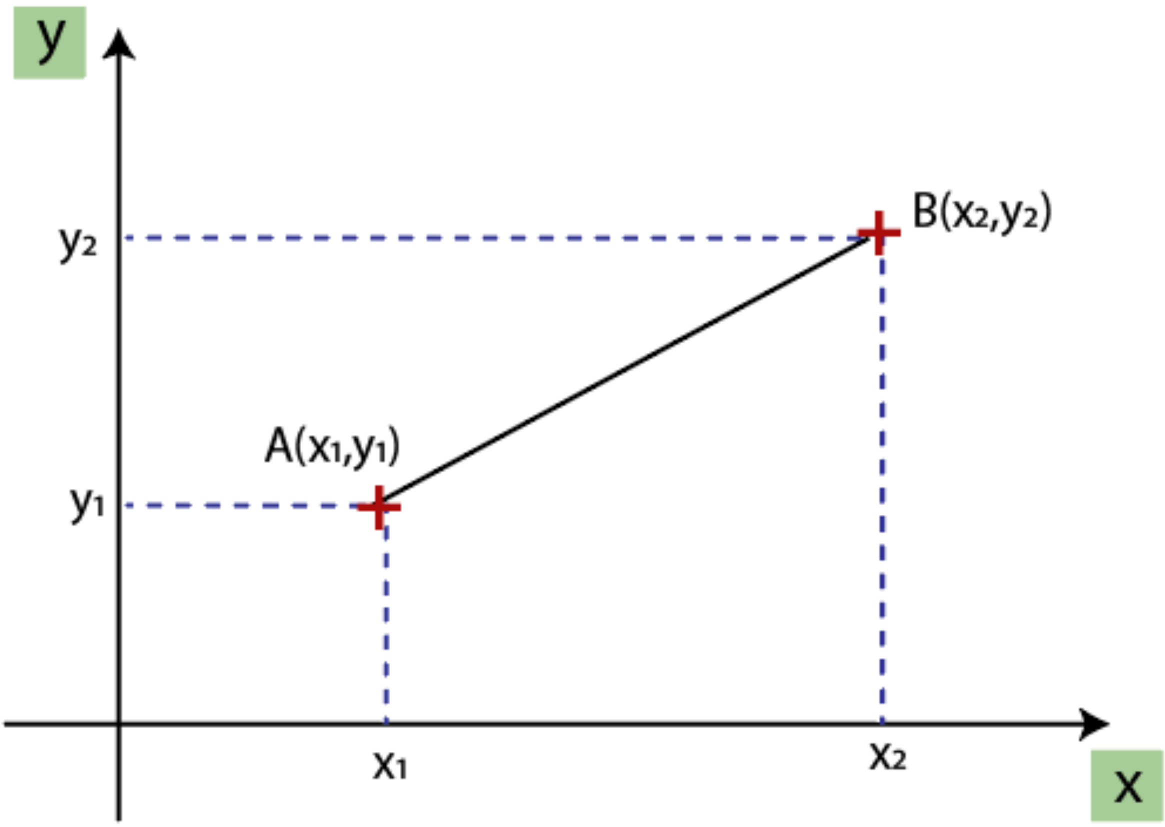
As we can see, the age and salary column values are not on the same scale. A machine learning model is based on **Euclidean distance**, and if we do not scale the variable, then it will cause some issue in our machine learning model.

Euclidean distance is given as:

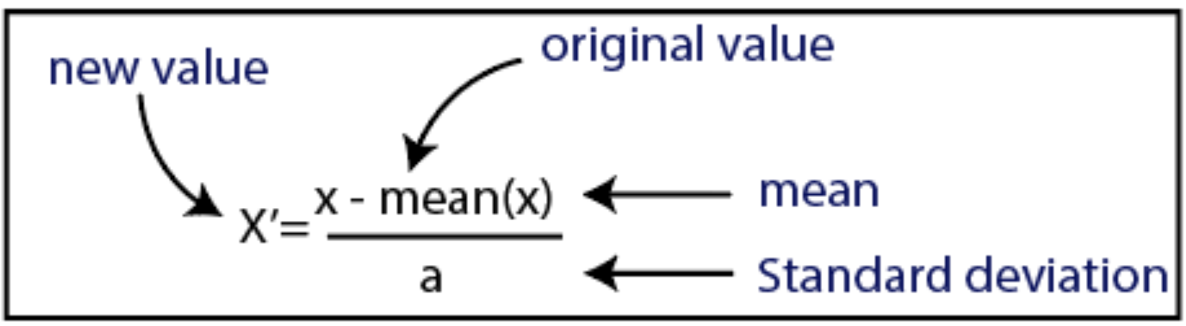


$$\text{Euclidean Distance Between A and B} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

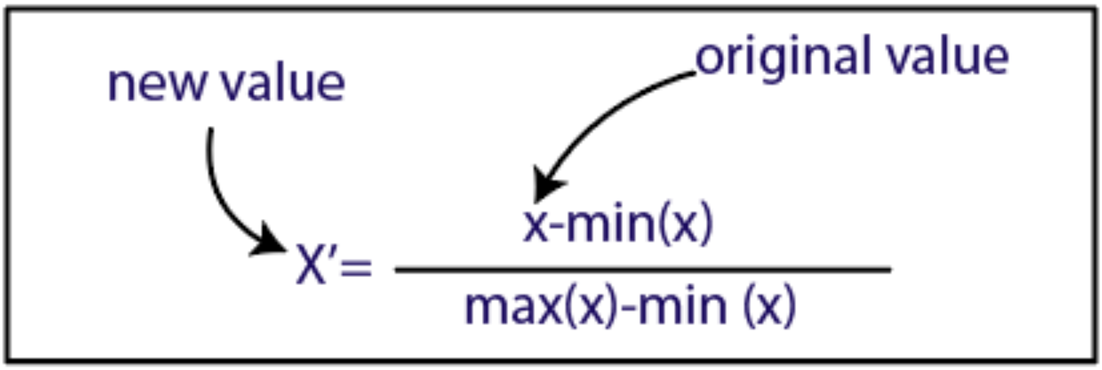
If we compute any two values from age and salary, then salary values will dominate the age values, and it will produce an incorrect result. So to remove this issue, we need to perform feature scaling for machine learning.

There are two ways to perform feature scaling in machine learning:

Standardization



Normalization



Here, we will use the standardization method for our dataset.

For feature scaling, we will import ***StandardScaler*** class of ***sklearn.preprocessing*** library as:

1. from sklearn.preprocessing import StandardScaler

Now, we will create the object of **StandardScaler** class for independent variables or features. And then we will fit and transform the training dataset.

1. st_x= StandardScaler()
2. x_train= st_x.fit_transform(x_train)

For test dataset, we will directly apply **transform()** function instead of **fit_transform()** because it is already done in training set.

1. x_test= st_x.transform(x_test)

Output:

By executing the above lines of code, we will get the scaled values for x_train and x_test as:

x_train:

x_train - NumPy array

	0	1	2	3	4
0	-1	1.73205	-0.57735	-0.294607	0.133962
1	1	-0.57735	-0.57735	-0.930959	1.22627
2	1	-0.57735	-0.57735	0.341745	-1.7415
3	-1	1.73205	-0.57735	-0.0589215	-0.999562
4	1	-0.57735	-0.57735	1.61445	1.41175
5	1	-0.57735	-0.57735	1.40233	0.113352
6	-1	-0.57735	1.73205	-0.718842	0.391581
7	-1	-0.57735	1.73205	-1.35519	-0.535848

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x_test:

x_test - NumPy array

	0	1	2	3	4
0	-1	1.73205	-0.57735	-2.41578	-0.906819
1	-1	-0.57735	1.73205	1.82657	2.24644

Format Resize ☑ Background color

Save and Close Close

As we can see in the above output, all the variables are scaled between values -1 to 1.

> *Note:* ***Here, we have not scaled the dependent variable because there are only two values 0 and 1. But if these variables will have more range of values, then we will also need to scale those variables.***

Combining all the steps:

Now, in the end, we can combine all the steps together to make our complete code more understandable.

```
# importing libraries
import numpy as nm
import matplotlib.pyplot as mtp
import pandas as pd

#importing datasets
data_set= pd.read_csv('Dataset.csv')

#Extracting Independent Variable
x= data_set.iloc[:, :-1].values

#Extracting Dependent variable
y= data_set.iloc[:, 3].values

#handling missing data(Replacing missing data with the mean value)
from sklearn.preprocessing import Imputer
imputer= Imputer(missing_values ='NaN', strategy='mean', axis = 0)

#Fitting imputer object to the independent varibles x.
imputerimputer= imputer.fit(x[:, 1:3])

#Replacing missing data with the calculated mean value
x[:, 1:3]= imputer.transform(x[:, 1:3])

#for Country Variable
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
label_encoder_x= LabelEncoder()
```

```
x[:, 0]= label_encoder_x.fit_transform(x[:, 0])

#Encoding for dummy variables
onehot_encoder= OneHotEncoder(categorical_features= [0])
x= onehot_encoder.fit_transform(x).toarray()

#encoding for purchased variable
labelencoder_y= LabelEncoder()
y= labelencoder_y.fit_transform(y)

# Splitting the dataset into training and test set.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.2, random_state=0)


#Feature Scaling of datasets
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x_train= st_x.fit_transform(x_train)
x_test= st_x.transform(x_test)
```

In the above code, we have included all the data preprocessing steps together. But there are some steps or lines of code which are not necessary for all machine learning models. So we can exclude them from our code to make it reusable for all models.

Supervised Machine Learning

Supervised learning is the types of machine learning in which machines are trained using well "labelled" training data, and on basis of that data, machines predict the output. The labelled data means some input data is already tagged with the correct output.

In supervised learning, the training data provided to the machines work as the supervisor that teaches the machines to predict the output correctly. It applies the same concept as a student learns in the supervision of the teacher.

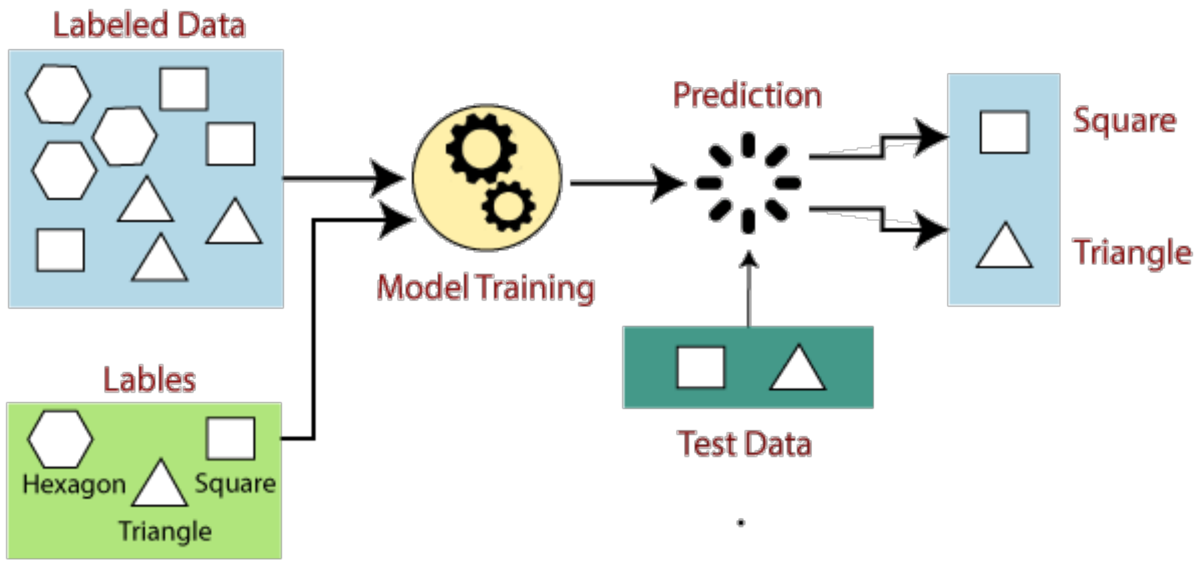
Supervised learning is a process of providing input data as well as correct output data to the machine learning model. The aim of a supervised learning algorithm is to **find a mapping function to map the input variable(x) with the output variable(y)**.

In the real-world, supervised learning can be used for **Risk Assessment, Image classification, Fraud Detection, spam filtering**, etc.

How Supervised Learning Works?

In supervised learning, models are trained using labelled dataset, where the model learns about each type of data. Once the training process is completed, the model is tested on the basis of test data (a subset of the training set), and then it predicts the output.

The working of Supervised learning can be easily understood by the below example and diagram:



Suppose we have a dataset of different types of shapes which includes square, rectangle, triangle, and Polygon. Now the first step is that we need to train the model for each shape.

- If the given shape has four sides, and all the sides are equal, then it will be labelled as a **Square**.
- If the given shape has three sides, then it will be labelled as a **triangle**.
- If the given shape has six equal sides then it will be labelled as **hexagon**.

Now, after training, we test our model using the test set, and the task of the model is to identify the shape.

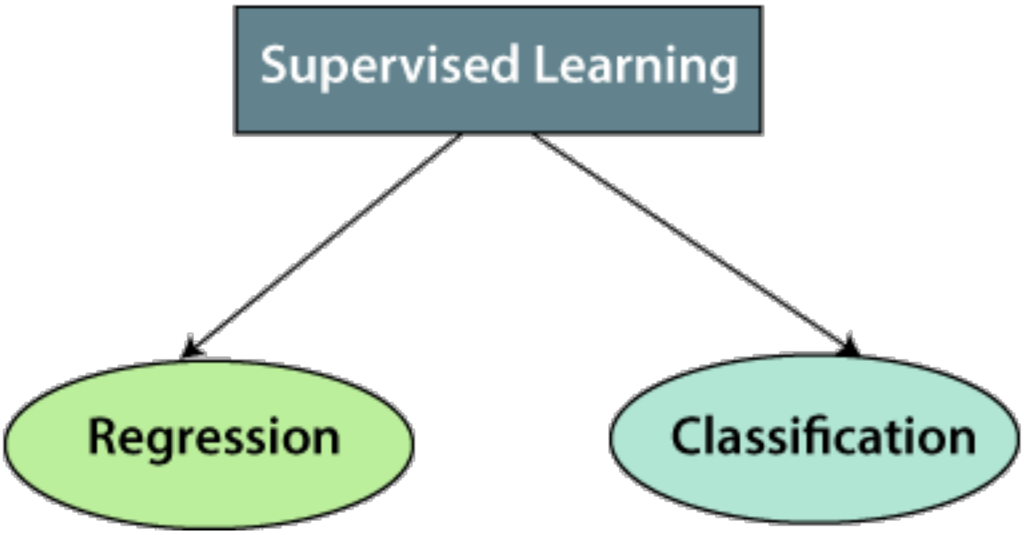
The machine is already trained on all types of shapes, and when it finds a new shape, it classifies the shape on the bases of a number of sides, and predicts the output.

Steps Involved in Supervised Learning:

- First Determine the type of training dataset
- Collect/Gather the labelled training data.
- Split the training dataset into training **dataset, test dataset, and validation dataset**.
- Determine the input features of the training dataset, which should have enough knowledge so that the model can accurately predict the output.
- Determine the suitable algorithm for the model, such as support vector machine, decision tree, etc.
- Execute the algorithm on the training dataset. Sometimes we need validation sets as the control parameters, which are the subset of training datasets.
- Evaluate the accuracy of the model by providing the test set. If the model predicts the correct output, which means our model is accurate.

Types of supervised Machine learning Algorithms:

Supervised learning can be further divided into two types of problems:



1. Regression

Regression algorithms are used if there is a relationship between the input variable and the output variable. It is used for the prediction of continuous variables, such as Weather forecasting, Market Trends, etc. Below are some popular Regression algorithms which come under supervised learning:

- Linear Regression
- Regression Trees
- Non-Linear Regression
- Bayesian Linear Regression
- Polynomial Regression

2. Classification

Classification algorithms are used when the output variable is categorical, which means there are two classes such as Yes-No, Male-Female, True-false, etc.

Spam Filtering,

- Random Forest
- Decision Trees
- Logistic Regression
- Support vector Machines

Advantages of Supervised learning:

- With the help of supervised learning, the model can predict the output on the basis of prior experiences.
- In supervised learning, we can have an exact idea about the classes of objects.
- Supervised learning model helps us to solve various real-world problems such as **fraud detection, spam filtering**, etc.

Disadvantages of supervised learning:

- Supervised learning models are not suitable for handling the complex tasks.
- Supervised learning cannot predict the correct output if the test data is different from the training dataset.
- Training required lots of computation times.
- In supervised learning, we need enough knowledge about the classes of object.

Unsupervised Machine Learning

In the previous topic, we learned supervised machine learning in which models are trained using labeled data under the supervision of training data. But there may be many cases in which we do not have labeled data and need to find the hidden patterns from the given dataset. So, to solve such types of cases in machine learning, we need unsupervised learning techniques.

What is Unsupervised Learning?

As the name suggests, unsupervised learning is a machine learning technique in which models are not supervised using training dataset. Instead, models itself find the hidden patterns and insights from the given data. It can be compared to learning which takes place in the human brain while learning new things. It can be defined as:

> *Unsupervised learning is a type of machine learning in which models are trained using unlabeled dataset and are allowed to act on that data without any supervision.*

Unsupervised learning cannot be directly applied to a regression or classification problem because unlike supervised learning, we have the input data but no corresponding output data. The goal of unsupervised learning is to **find the underlying structure of dataset, group that data according to similarities, and represent that dataset in a compressed format**.

Example: Suppose the unsupervised learning algorithm is given an input dataset containing images of different types of cats and dogs. The algorithm is never trained upon the given dataset, which means it does not have any idea about the features of the dataset. The task of the unsupervised learning algorithm is to identify the image features on their own. Unsupervised learning algorithm will perform this task by clustering the image dataset into the groups according to similarities between images.

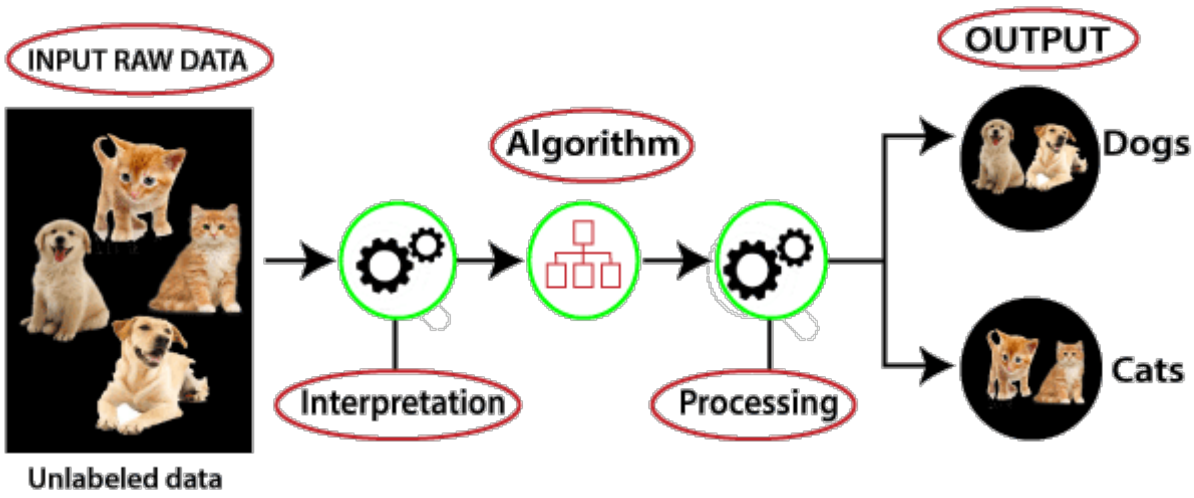
Why use Unsupervised Learning?

Below are some main reasons which describe the importance of Unsupervised Learning:

- Unsupervised learning is helpful for finding useful insights from the data.
- Unsupervised learning is much similar as a human learns to think by their own experiences, which makes it closer to the real AI.
- Unsupervised learning works on unlabeled and uncategorized data which make unsupervised learning more important.
- In real-world, we do not always have input data with the corresponding output so to solve such cases, we need unsupervised learning.

Working of Unsupervised Learning

Working of unsupervised learning can be understood by the below diagram:

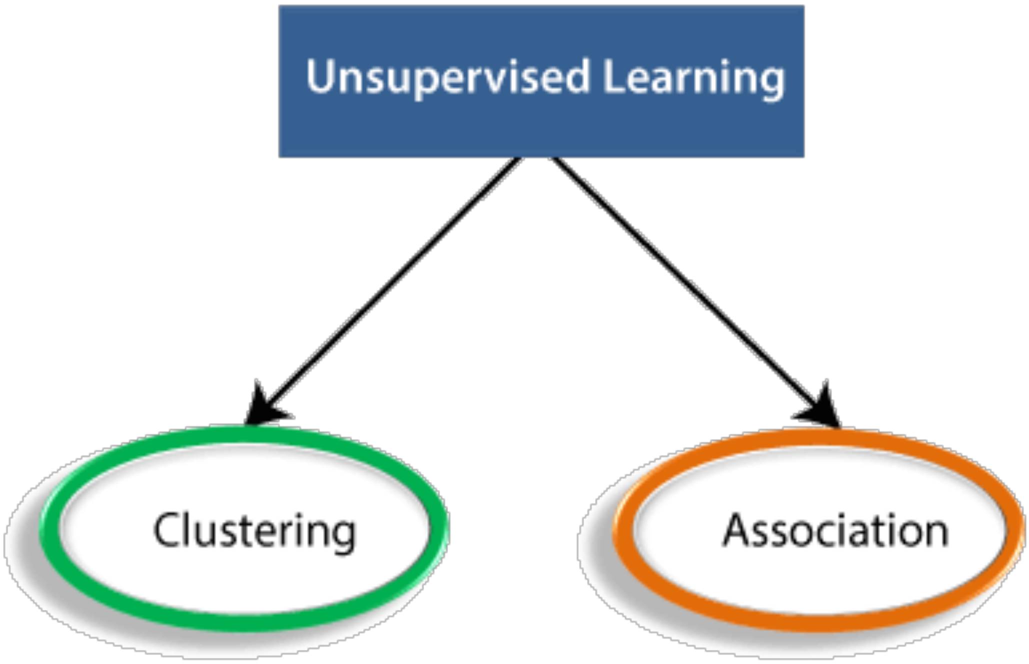


Here, we have taken an unlabeled input data, which means it is not categorized and corresponding outputs are also not given. Now, this unlabeled input data is fed to the machine learning model in order to train it. Firstly, it will interpret the raw data to find the hidden patterns from the data and then will apply suitable algorithms such as k-means clustering, Decision tree, etc.

Once it applies the suitable algorithm, the algorithm divides the data objects into groups according to the similarities and difference between the objects.

Types of Unsupervised Learning Algorithm:

The unsupervised learning algorithm can be further categorized into two types of problems:



- **Clustering**: Clustering is a method of grouping the objects into clusters such that objects with most similarities remains into a group and has less or no similarities with the objects of another group. Cluster analysis finds the commonalities between the data objects and categorizes them as per the presence and absence of those commonalities.
- **Association**: An association rule is an unsupervised learning method which is used for finding the relationships between variables in the large database. It determines the set of items that occurs together in the dataset. Association rule makes marketing strategy more effective. Such as people who buy X item

(suppose a bread) are also tend to purchase Y (Butter/Jam) item. A typical example of Association rule is Market Basket Analysis.

Unsupervised Learning algorithms:

Below is the list of some popular unsupervised learning algorithms:

- **K-means clustering**
- **KNN (k-nearest neighbors)**
- **Hierarchal clustering**
- **Anomaly detection**
- **Neural Networks**
- **Principle Component Analysis**
- **Independent Component Analysis**
- **Apriori algorithm**
- **Singular value decomposition**

Advantages of Unsupervised Learning

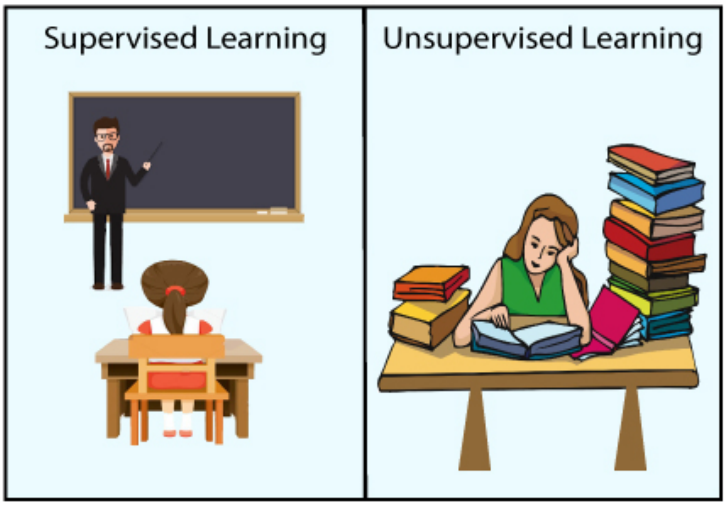
- Unsupervised learning is used for more complex tasks as compared to supervised learning because, in unsupervised learning, we don't have labeled input data.
- Unsupervised learning is preferable as it is easy to get unlabeled data in comparison to labeled data.

Disadvantages of Unsupervised Learning

- Unsupervised learning is intrinsically more difficult than supervised learning as it does not have corresponding output.
- The result of the unsupervised learning algorithm might be less accurate as input data is not labeled, and algorithms do not know the exact output in advance.

Difference between Supervised and Unsupervised Learning

Supervised and Unsupervised learning are the two techniques of machine learning. But both the techniques are used in different scenarios and with different datasets. Below the explanation of both learning methods along with their difference table is given.



Supervised Machine Learning:

Supervised learning is a machine learning method in which models are trained using labeled data. In supervised learning, models need to find the mapping function to map the input variable (X) with the output variable (Y).

$$\boxed{Y = f(X)}$$

Supervised learning needs supervision to train the model, which is similar to as a student learns things in the presence of a teacher. Supervised learning can be used for two types of problems: **Classification** and **Regression**.

Example: Suppose we have an image of different types of fruits. The task of our supervised learning model is to identify the fruits and classify them accordingly. So to identify the image in supervised learning, we will give the input data as well as output for that, which means we will train the model by the shape, size, color, and taste of each fruit. Once the training is completed, we will test the model by giving the new set of fruit. The model will identify the fruit and predict the output using a suitable algorithm.

Unsupervised Machine Learning:

Unsupervised learning is another machine learning method in which patterns inferred from the unlabeled input data. The goal of unsupervised learning is to find the structure and patterns from the input data. Unsupervised learning does not need any supervision. Instead, it finds patterns from the data by its own.

Unsupervised learning can be used for two types of problems: **Clustering** and **Association**.

Example: To understand the unsupervised learning, we will use the example given above. So unlike supervised learning, here we will not provide any supervision to the model. We will just provide the input dataset to the model and allow the model to find the patterns from the data. With the help of a suitable algorithm, the model will train itself and divide the fruits into different groups according to the most similar features between them. The main differences between Supervised and Unsupervised learning are given below:

Supervised Learning	Unsupervised Learning
Supervised learning algorithms are trained using labeled data.	Unsupervised learning algorithms are trained using unlabeled data.
Supervised learning model takes direct feedback to check if it is predicting correct output or not.	Unsupervised learning model does not take any feedback.
Supervised learning model predicts the output.	Unsupervised learning model finds the hidden patterns in data.
In supervised learning, input data is provided to the model along with the output.	In unsupervised learning, only input data is provided to the model.
The goal of supervised learning is to train the model so that it can predict the output when it is given new data.	The goal of unsupervised learning is to find the hidden patterns and useful insights from the unknown dataset.
Supervised learning needs supervision to train the model.	Unsupervised learning does not need any supervision to train the model.
Supervised learning can be categorized in **Classification** and **Regression** problems.	Unsupervised Learning can be classified in **Clustering** and **Associations** problems.
Supervised learning can be used for those cases where we know the input as well as corresponding outputs.	Unsupervised learning can be used for those cases where we have only input data and no corresponding output data.
Supervised learning model produces an accurate result.	Unsupervised learning model may give less accurate result as compared to supervised learning.
Supervised learning is not close to true Artificial intelligence as in this, we first train the model for each data, and then only it can predict the correct output.	Unsupervised learning is more close to the true Artificial Intelligence as it learns similarly as a child learns daily routine things by his experiences.
It includes various algorithms such as Linear Regression, Logistic Regression, Support Vector Machine, Multi-class Classification, Decision tree, Bayesian Logic, etc.	It includes various algorithms such as Clustering, KNN, and Apriori algorithm.

Regression Analysis in Machine learning

Regression analysis is a statistical method to model the relationship between a dependent (target) and independent (predictor) variables with one or more independent variables. More specifically, Regression analysis helps us to understand how the value of the dependent variable is changing corresponding to an independent variable when other independent variables are held fixed. It predicts continuous/real values such as **temperature, age, salary, price,** etc.

We can understand the concept of regression analysis using the below example:

Example: Suppose there is a marketing company A, who does various advertisement every year and get sales on that. The below list shows the advertisement made by the company in the last 5 years and the corresponding sales:

Advertisement	Sales
$90	$1000
$120	$1300
$150	$1800
$100	$1200
$130	$1380
$200	??

Now, the company wants to do the advertisement of $200 in the year 2019 **and wants to know the prediction about the sales for this year**. So to solve such type of prediction problems in machine learning, we need regression analysis.

Regression is a supervised learning technique

which helps in finding the correlation between variables and enables us to predict the continuous output variable based on the one or more predictor variables. It is mainly used for **prediction, forecasting, time series modeling, and determining the causal-effect relationship between variables**.

In Regression, we plot a graph between the variables which best fits the given datapoints, using this plot, the machine learning model can make predictions about the data. In simple words, **"*Regression shows a line or curve that passes through all the datapoints on target-predictor graph in such a way that the vertical***

distance between the datapoints and the regression line is minimum." The distance between datapoints and line tells whether a model has captured a strong relationship or not.

Some examples of regression can be as:

- Prediction of rain using temperature and other factors
- Determining Market trends
- Prediction of road accidents due to rash driving.

Terminologies Related to the Regression Analysis:

- **Dependent Variable:** The main factor in Regression analysis which we want to predict or understand is called the dependent variable. It is also called **target variable**.
- **Independent Variable:** The factors which affect the dependent variables or which are used to predict the values of the dependent variables are called independent variable, also called as a **predictor**.
- **Outliers:** Outlier is an observation which contains either very low value or very high value in comparison to other observed values. An outlier may hamper the result, so it should be avoided.
- **Multicollinearity:** If the independent variables are highly correlated with each other than other variables, then such condition is called Multicollinearity. It should not be present in the dataset, because it creates problem while ranking the most affecting variable.
- **Underfitting and Overfitting:** If our algorithm works well with the training dataset but not well with test dataset, then such problem is called **Overfitting**. And if our algorithm does not perform well even with training dataset, then such problem is called **underfitting**.

Why do we use Regression Analysis?

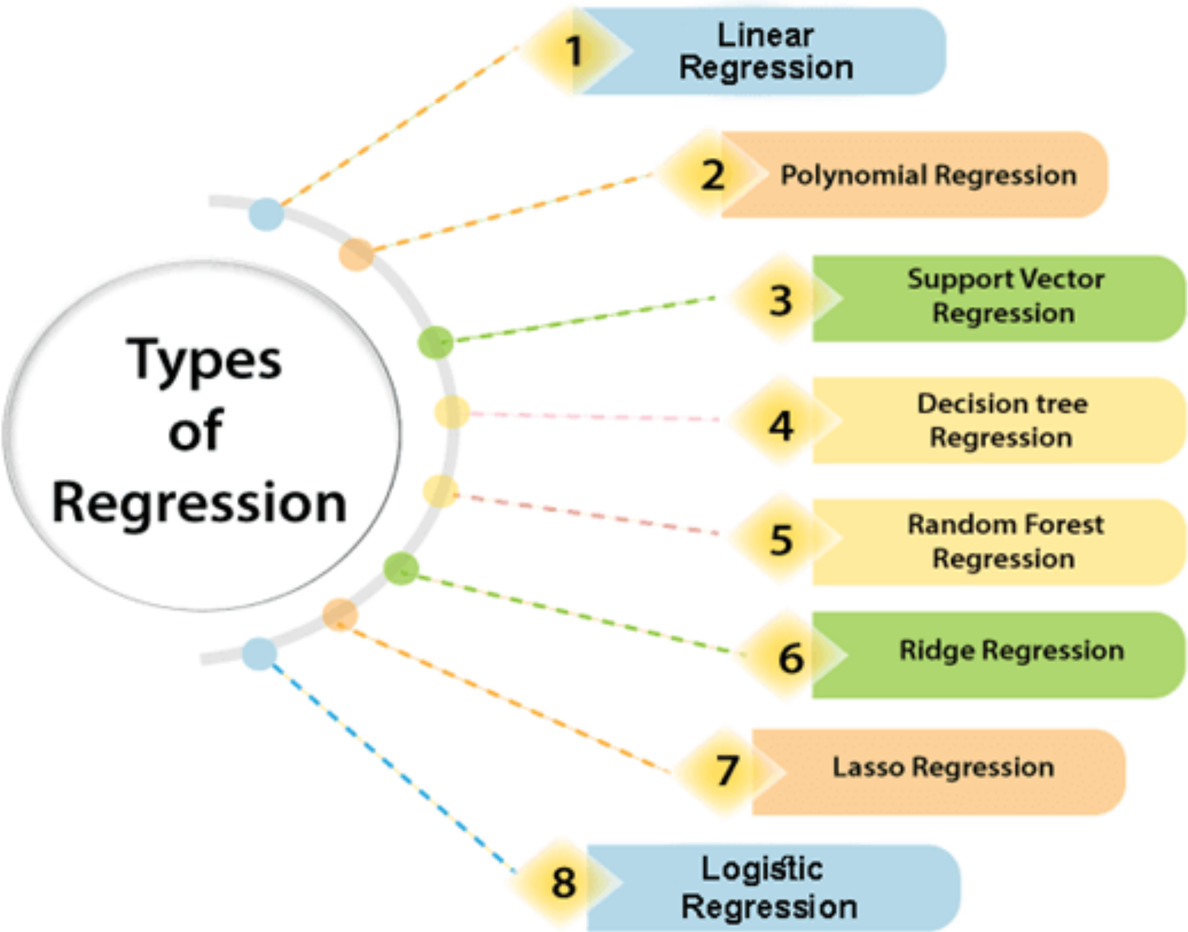
As mentioned above, Regression analysis helps in the prediction of a continuous variable. There are various scenarios in the real world where we need some future predictions such as weather condition, sales prediction, marketing trends, etc., for such case we need some technology which can make predictions more accurately. So for such case we need Regression analysis which is a statistical method and used in machine learning and data science. Below are some other reasons for using Regression analysis:

- Regression estimates the relationship between the target and the independent variable.
- It is used to find the trends in data.
- It helps to predict real/continuous values.
- By performing the regression, we can confidently determine the **most important factor, the least important factor, and how each factor is affecting the other factors**.

Types of Regression

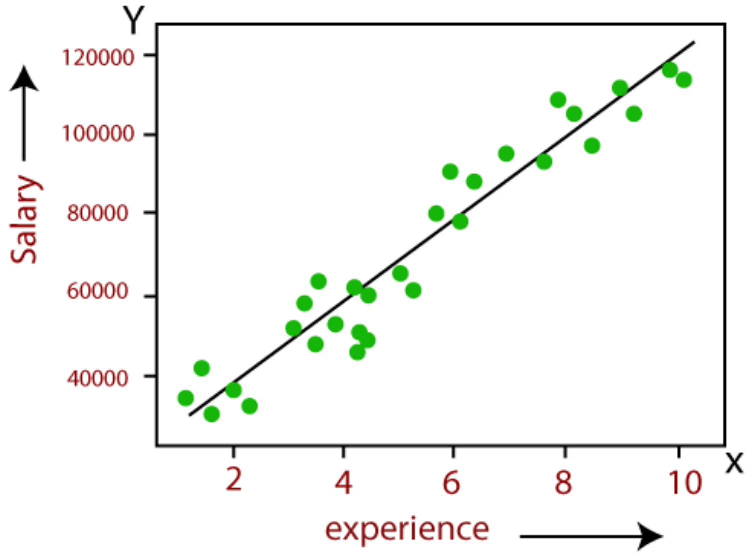
There are various types of regressions which are used in data science and machine learning. Each type has its own importance on different scenarios, but at the core, all the regression methods analyze the effect of the independent variable on dependent variables. Here we are discussing some important types of regression which are given below:

- **Linear Regression**
- **Logistic Regression**
- **Polynomial Regression**
- **Support Vector Regression**
- **Decision Tree Regression**
- **Random Forest Regression**
- **Ridge Regression**
- **Lasso Regression:**



Linear Regression:

- Linear regression is a statistical regression method which is used for predictive analysis.
- It is one of the very simple and easy algorithms which works on regression and shows the relationship between the continuous variables.
- It is used for solving the regression problem in machine learning.
- Linear regression shows the linear relationship between the independent variable (X-axis) and the dependent variable (Y-axis), hence called linear regression.
- If there is only one input variable (x), then such linear regression is called **simple linear regression**. And if there is more than one input variable, then such linear regression is called **multiple linear regression**.
- The relationship between variables in the linear regression model can be explained using the below image. Here we are predicting the salary of an employee on the basis of **the year of experience**.



- Below is the mathematical equation for Linear regression:

1. Y= aX+b

**Here, Y = dependent variables (target variables),
X= Independent variables (predictor variables),
a and b are the linear coefficients**

Some popular applications of linear regression are:

- **Analyzing trends and sales estimates**
- **Salary forecasting**
- **Real estate prediction**
- **Arriving at ETAs in traffic.**

Logistic Regression:

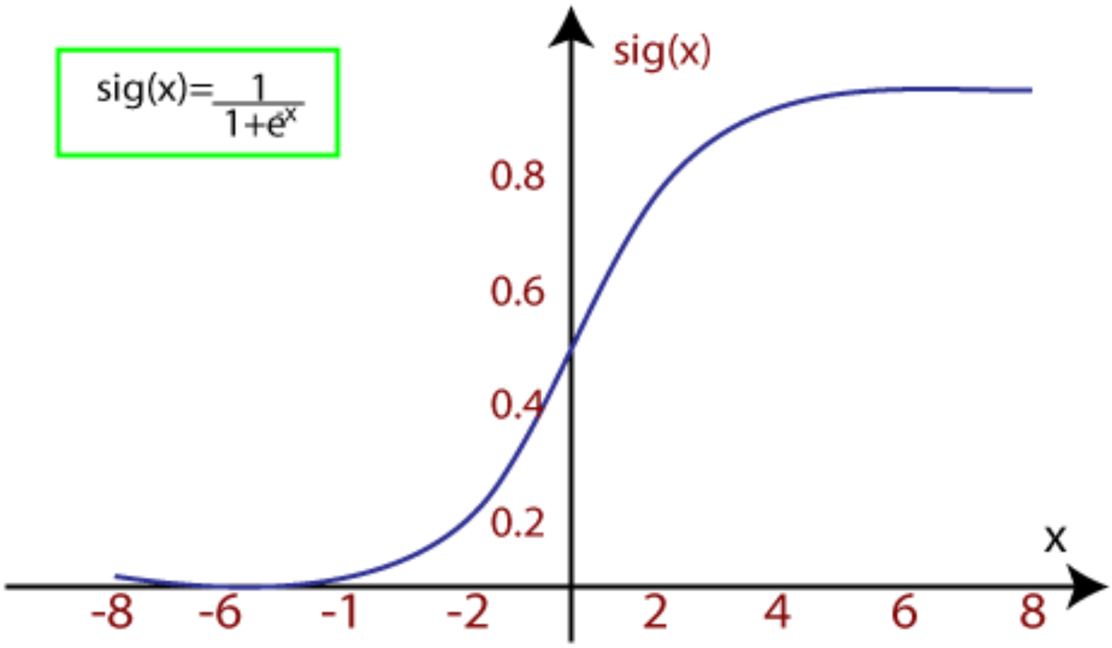
- Logistic regression is another supervised learning algorithm which is used to solve the classification problems. In **classification problems**, we have dependent variables in a binary or discrete format such as 0 or 1.
- Logistic regression algorithm works with the categorical variable such as 0 or 1, Yes or No, True or False, Spam or not spam, etc.
- It is a predictive analysis algorithm which works on the concept of probability.
- Logistic regression is a type of regression, but it is different from the linear regression algorithm in the term how they are used.

- Logistic regression uses **sigmoid function** or logistic function which is a complex cost function. This sigmoid function is used to model the data in logistic regression. The function can be represented as:

$$f(x)=\frac{1}{1+e^{-x}}$$

- f(x)= Output between the 0 and 1 value.
- x= input to the function
- e= base of natural logarithm.

When we provide the input values (data) to the function, it gives the S-curve as follows:



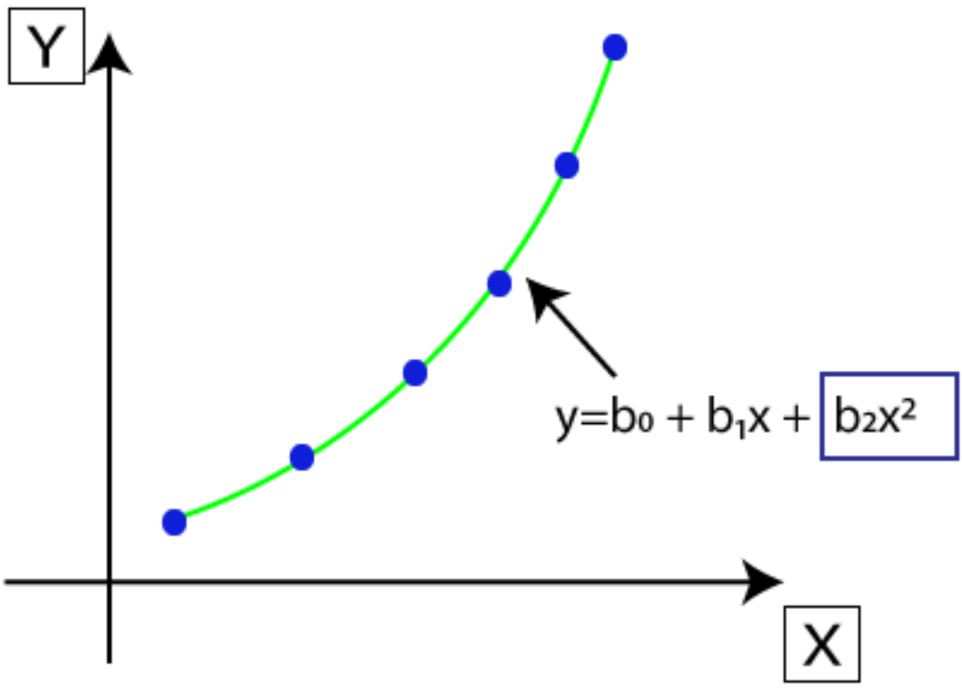
- It uses the concept of threshold levels, values above the threshold level are rounded up to 1, and values below the threshold level are rounded up to 0.

There are three types of logistic regression:

- **Binary(0/1, pass/fail)**
- **Multi(cats, dogs, lions)**
- **Ordinal(low, medium, high)**

Polynomial Regression:

- Polynomial Regression is a type of regression which models the **non-linear dataset** using a linear model.
- It is similar to multiple linear regression, but it fits a non-linear curve between the value of x and corresponding conditional values of y.
- Suppose there is a dataset which consists of datapoints which are present in a non-linear fashion, so for such case, linear regression will not best fit to those datapoints. To cover such datapoints, we need Polynomial regression.
- **In Polynomial regression, the original features are transformed into polynomial features of given degree and then modeled using a linear model.** Which means the datapoints are best fitted using a polynomial line.



- The equation for polynomial regression also derived from linear regression equation that means Linear regression equation $Y= b_0+ b_1x$, is transformed into Polynomial regression equation $Y= b_0+b_1x+ b_2x^2+ b_3x^3+.....+ b_nx^n$.
- Here Y is the **predicted/target output, b_0, b_1,... b_n are the regression coefficients**. x is our **independent/input variable**.
- The model is still linear as the coefficients are still linear with quadratic

> *Note:* ***This is different from Multiple Linear regression in such a way that in Polynomial regression, a single element has different degrees instead of multiple variables with the same degree.***

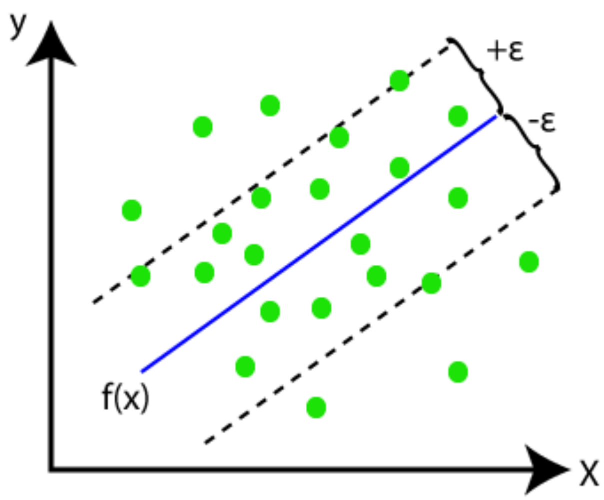
Support Vector Regression:

Support Vector Machine is a supervised learning algorithm which can be used for regression as well as classification problems. So if we use it for regression problems, then it is termed as Support Vector Regression.

Support Vector Regression is a regression algorithm which works for continuous variables. Below are some keywords which are used in **Support Vector Regression**:

- **Kernel:** It is a function used to map a lower-dimensional data into higher dimensional data.
- **Hyperplane:** In general SVM, it is a separation line between two classes, but in SVR, it is a line which helps to predict the continuous variables and cover most of the datapoints.
- **Boundary line:** Boundary lines are the two lines apart from hyperplane, which creates a margin for datapoints.
- **Support vectors:** Support vectors are the datapoints which are nearest to the hyperplane and opposite class.

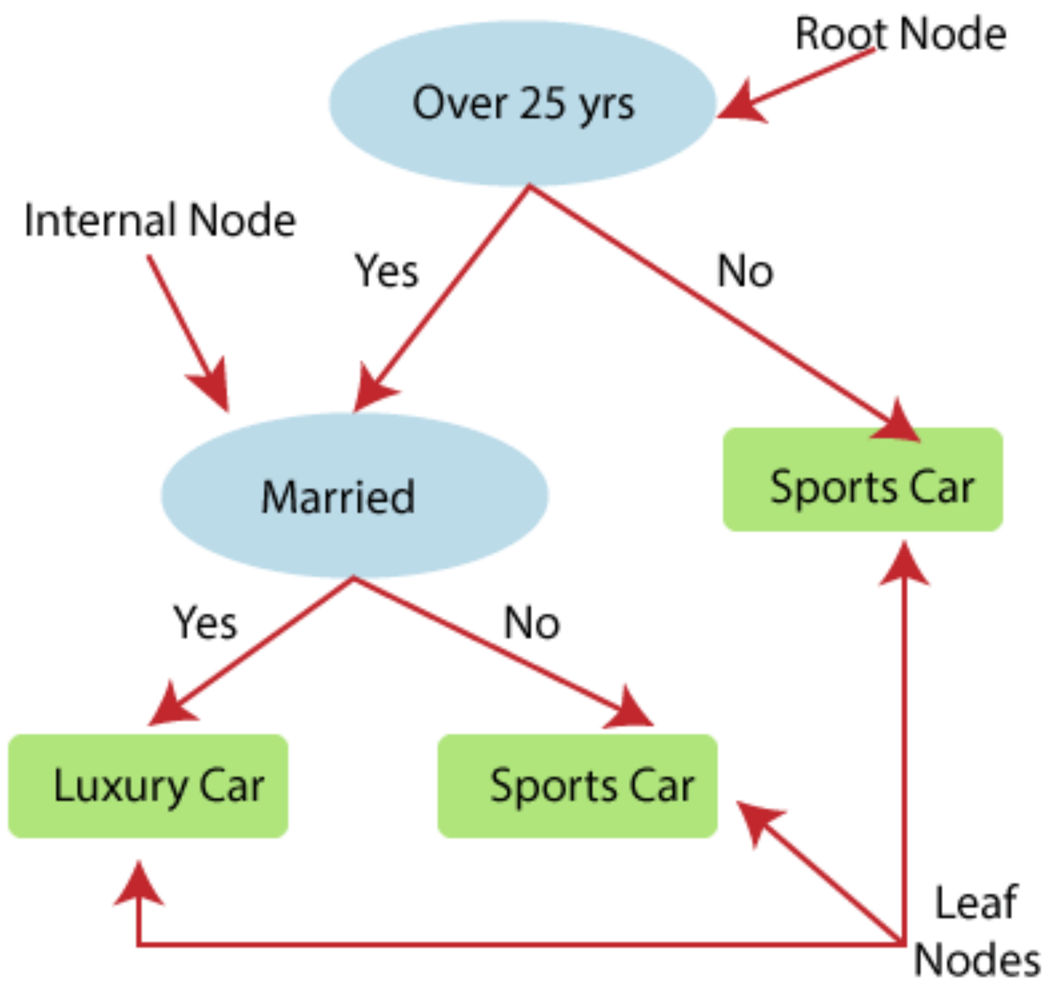
In SVR, we always try to determine a hyperplane with a maximum margin, so that maximum number of datapoints are covered in that margin. ***The main goal of SVR is to consider the maximum datapoints within the boundary lines and the hyperplane (best-fit line) must contain a maximum number of datapoints***. Consider the below image:



Here, the blue line is called hyperplane, and the other two lines are known as boundary lines.

Decision Tree Regression:

- Decision Tree is a supervised learning algorithm which can be used for solving both classification and regression problems.
- It can solve problems for both categorical and numerical data
- Decision Tree regression builds a tree-like structure in which each internal node represents the "test" for an attribute, each branch represent the result of the test, and each leaf node represents the final decision or result.
- A decision tree is constructed starting from the root node/parent node (dataset), which splits into left and right child nodes (subsets of dataset). These child nodes are further divided into their children node, and themselves become the parent node of those nodes. Consider the below image:

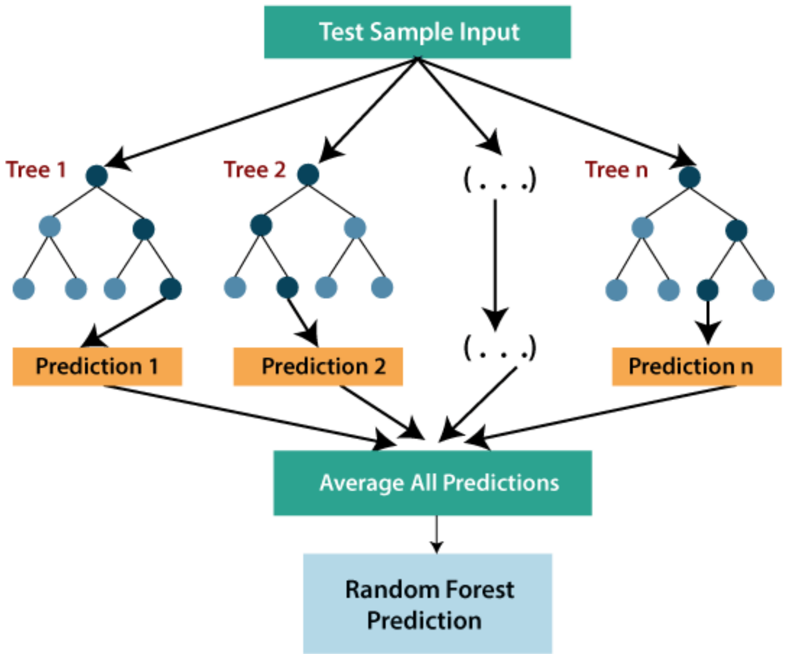


Above image showing the example of Decision Tee regression, here, the model is trying to predict the choice of a person between Sports cars or Luxury car.

- Random forest is one of the most powerful supervised learning algorithms which is capable of performing regression as well as classification tasks.
- The Random Forest regression is an ensemble learning method which combines multiple decision trees and predicts the final output based on the average of each tree output. The combined decision trees are called as base models, and it can be represented more formally as:

$$g(x) = f_0(x) + f_1(x) + f_2(x) + \ldots.$$

- Random forest uses **Bagging or Bootstrap Aggregation** technique of ensemble learning in which aggregated decision tree runs in parallel and do not interact with each other.
- With the help of Random Forest regression, we can prevent Overfitting in the model by creating random subsets of the dataset.



Ridge Regression:

- Ridge regression is one of the most robust versions of linear regression in which a small amount of bias is introduced so that we can get better long term predictions.
- The amount of bias added to the model is known as **Ridge Regression penalty**. We can compute this penalty term by multiplying with the lambda to the squared weight of each individual features.

- The equation for ridge regression will be:

$$L(x, y) = Min(\sum_{i=1}^{n}(y_i - w_i x_i)^2 + \lambda \sum_{i=1}^{n}(w_i)^2)$$

- A general linear or polynomial regression will fail if there is high collinearity between the independent variables, so to solve such problems, Ridge regression can be used.
- Ridge regression is a regularization technique, which is used to reduce the complexity of the model. It is also called as **L2 regularization**.
- It helps to solve the problems if we have more parameters than samples.

Lasso Regression:

- Lasso regression is another regularization technique to reduce the complexity of the model.
- It is similar to the Ridge Regression except that penalty term contains only the absolute weights instead of a square of weights.
- Since it takes absolute values, hence, it can shrink the slope to 0, whereas Ridge Regression can only shrink it near to 0.
- It is also called as **L1 regularization**. The equation for Lasso regression will be:

$$L(x, y)= Min(\sum_{i=1}^{n}(y_i - w_i x_i)^2 + \lambda \sum_{i=1}^{n} |\mathbf{w_i}\ |)$$