UNIT-2

CLASSIFICATION AND CLUSTERING

Machine Learning algorithms are generally categorized based upon the type of output variable and the type of problem that needs to be addressed. These algorithms are broadly divided into three types i.e. Regression, Clustering, and Classification. Regression and Classification are types of supervised learning algorithms while Clustering is a type of unsupervised algorithm.

When the output variable is continuous, then it is a regression problem whereas when it contains discrete values, it is a classification problem. Clustering algorithms are generally used when we need to create the clusters based on the characteristics of the data points.

Classification

Classification is a type of supervised machine learning algorithm. For any given input, the classification algorithms help in the prediction of the class of the output variable. There can be multiple types of classifications like binary classification, multi-class classification, etc. It depends upon the number of classes in the output variable.

Types of Classification algorithms

Logistic Regression: – It is one of the linear models which can be used for classification. It uses the sigmoid function to calculate the probability of a certain event occurring. It is an ideal method for the classification of binary variables.

K-Nearest Neighbours (kNN): – It uses distance metrics like Euclidean distance, Manhattan distance, etc. to calculate the distance of one data point from every other data point. To classify the output, it takes a majority vote from k nearest neighbors of each data point.

Decision Trees: – It is a non-linear model that overcomes a few of the drawbacks of linear algorithms like Logistic regression. It builds the classification model in the form of a tree structure that includes nodes and leaves. This algorithm involves multiple if-else statements which help in breaking down the structure into smaller structures and eventually providing the final outcome. It can be used for regression as well as classification problems.

Random Forest: – It is an ensemble learning method that involves multiple decision trees to predict the outcome of the target variable. Each decision tree provides its own outcome. In the case of the classification problem, it takes the majority vote of these multiple decision trees to classify the final outcome. In the case of the regression problem, it takes the average of the values predicted by the decision trees.

Naïve Bayes: – It is an algorithm that is based upon Bayes' theorem. It assumes that any particular feature is independent of the inclusion of other features. i.e. They are not correlated to one another. It generally does not work well with complex data due to this assumption as in most of the data sets there exists some kind of relationship between the features.

Support Vector Machine: – It represents the data points in multi-dimensional space. These data points are then segregated into classes with the help of hyperplanes. It plots an n-dimensional space for the n number of features in the dataset and then tries to create the hyperplanes such that it divides the data points with maximum margin.

Clustering

Clustering is a type of unsupervised machine learning algorithm. It is used to group data points having similar characteristics as clusters. Ideally, the data points in the same cluster should exhibit similar properties and the points in different clusters should be as dissimilar as possible.

Clustering is divided into two groups – hard clustering and soft clustering. In hard clustering, the data point is assigned to one of the clusters only whereas in soft clustering, it provides a probability likelihood of a data point to be in each of the clusters.

Types of Clustering algorithms

K-Means Clustering: – It initializes a pre-defined number of k clusters and uses distance metrics to calculate the distance of each data point from the centroid of each cluster. It assigns the data points into one of the k clusters based on its distance.

Agglomerative Hierarchical Clustering (Bottom-Up Approach): – It considers each data point as a cluster and merges these data points on the basis of distance metric and the criterion which is used for linking these clusters.

Divisive Hierarchical Clustering (Top-Down Approach): – It initializes with all the data points as one cluster and splits these data points on the basis of distance metric and

the criterion. Agglomerative and Divisive clustering can be represented as a dendrogram and the number of clusters to be selected by referring to the same.

DBSCAN (Density-based Spatial Clustering of Applications with Noise): – It is a density-based clustering method. Algorithms like K-Means work well on the clusters that are fairly separated and create clusters that are spherical in shape. DBSCAN is used when the data is in arbitrary shape and it is also less sensitive to the outliers. It groups the data points that have many neighbouring data points within a certain radius.

OPTICS (Ordering Points to Identify Clustering Structure): – It is another type of density-based clustering method and it is similar in process to DBSCAN except that it considers a few more parameters. But it is more computationally complex than DBSCAN. Also, it does not separate the data points into clusters, but it creates a reachability plot which can help in the interpretation of creating clusters.

BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies): – It creates clusters by generating a summary of the data. It works well with huge datasets as it first summarises the data and then uses the same to create clusters. However, it can only deal with numeric attributes that can be represented in space.

Difference Between Clustering and Classification

Characteristics	Classification	Clustering
Type	Supervised	Unsupervised
Process	Classifying the input data as one of the class labels from the output variable.	Data points are grouped as clusters based on their similarities.
Prediction	Classification involves the prediction of the input variable based on the model building.	Clustering is generally used to analyze the data and draw inferences from it for better decision making
Splitting of data	Classification algorithms need the data to be split as training and test data for predicting and evaluating the model.	Clustering algorithms do not need the splitting of data for its use.

Data Label	Classification algorithms deal with labelled data	Clustering algorithms deal with unlabeled data.
Stages	Classification process involves two stages – Training and Testing.	Clustering process involves only the grouping of data.
Complexity	High complexity because classification deals with a greater number of stages.	Low complexity because Clustering algorithms whose aim is only to group the data.

Classification and Prediction

There are two forms of data analysis that can be used for extracting models describing important classes or to predict future data trends. These two forms are as follows −

- Classification
- Prediction

Classification models predict categorical class labels; and prediction models predict continuous valued functions. For example, we can build a classification model to categorize bank loan applications as either safe or risky, or a prediction model to predict the expenditures in dollars of potential customers on computer equipment given their income and occupation.

Example - Classification

Following are the examples of cases where the data analysis task is Classification −

- A bank loan officer wants to analyze the data in order to know which customer (loan applicant) are risky or which are safe.
- A marketing manager at a company needs to analyze a customer with a given profile, who will buy a new computer.

In both of the above examples, a model or classifier is constructed to predict the categorical labels. These labels are risky or safe for loan application data and yes or no for marketing data.

What is prediction?

Following are the examples of cases where the data analysis task is Prediction − Suppose the marketing manager needs to predict how much a given customer will spend during a sale at his company. In this example we are bothered to predict a numeric value. Therefore the data analysis task is an example of numeric prediction. In this case, a model or a predictor will be constructed that predicts a continuous-valued-function or ordered value.

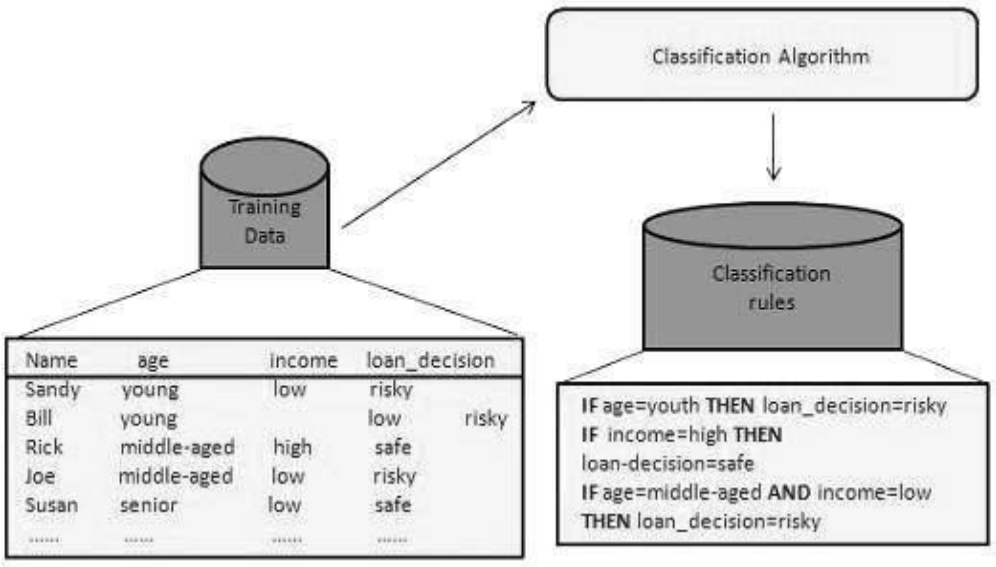
Classifier Model

The Data Classification process includes two steps −

- Building the Classifier or Model
- Using Classifier for Classification

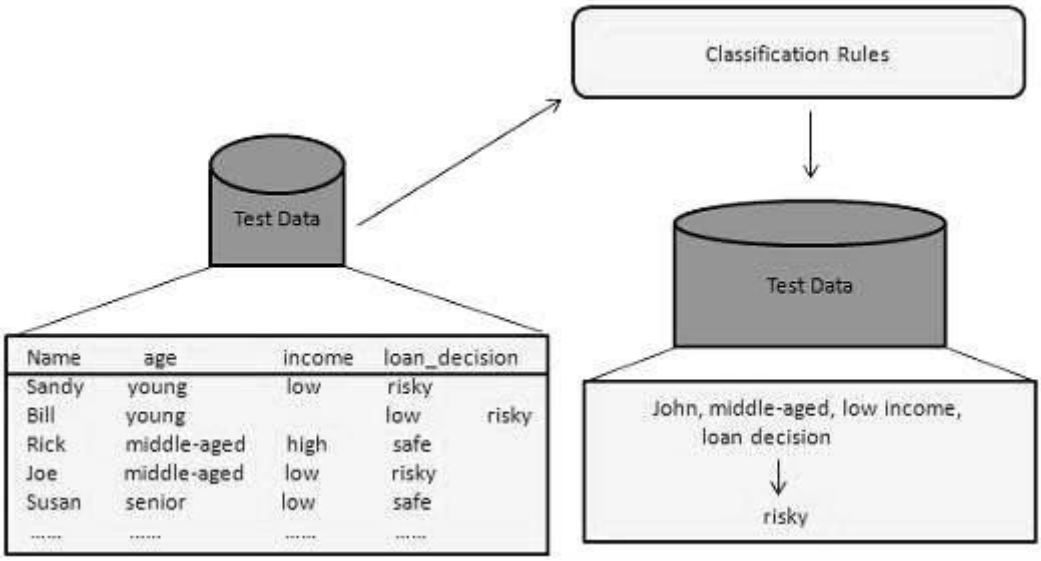
Building the Classifier or Model

- This step is the learning step or the learning phase.
- In this step the classification algorithms build the classifier.
- The classifier is built from the training set made up of database tuples and their associated class labels.
- Each tuple that constitutes the training set is referred to as a category or class. These tuples can also be referred to as sample, object or data points.



Using Classifier for Classification

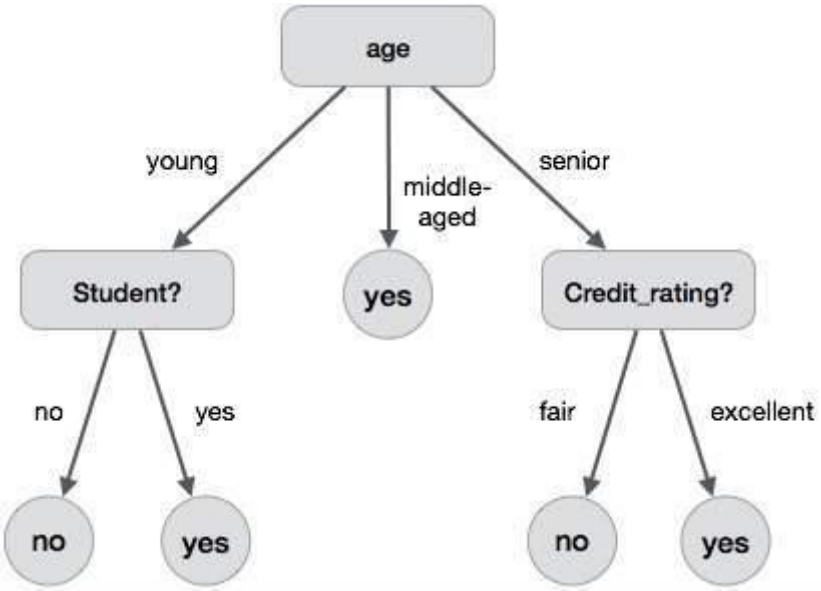
In this step, the classifier is used for classification. Here the test data is used to estimate the accuracy of classification rules. The classification rules can be applied to the new data tuples if the accuracy is considered acceptable.



Decision Tree Induction

A decision tree is a structure that includes a root node, branches, and leaf nodes. Each internal node denotes a test on an attribute, each branch denotes the outcome of a test, and each leaf node holds a class label. The topmost node in the tree is the root node.

The following decision tree is for the concept buy computer that indicates whether a customer at a company is likely to buy a computer or not. Each internal node represents a test on an attribute. Each leaf node represents a class.



The benefits of having a decision tree are as follows −

- It does not require any domain knowledge.
- It is easy to comprehend.
- The learning and classification steps of a decision tree are simple and fast.

Bayesian classification

It is based on Bayes' Theorem. Bayesian classifiers are the statistical classifiers. Bayesian classifiers can predict class membership probabilities such as the probability that a given tuple belongs to a particular class.

Baye's Theorem

Bayes' Theorem is named after Thomas Bayes. There are two types of probabilities −

- Posterior Probability [P(H/X)]
- Prior Probability [P(H)]

where X is data tuple and H is some hypothesis.

According to Bayes' Theorem, P(H/X)= P(X/H)P(H) / P(X)

Bayesian Belief Network

Bayesian Belief Networks specify joint conditional probability distributions. They are also known as Belief Networks, Bayesian Networks, or Probabilistic Networks.

- A Belief Network allows class conditional independencies to be defined between subsets of variables.
- It provides a graphical model of causal relationship on which learning can be performed.
- We can use a trained Bayesian Network for classification.

There are two components that define a Bayesian Belief Network −

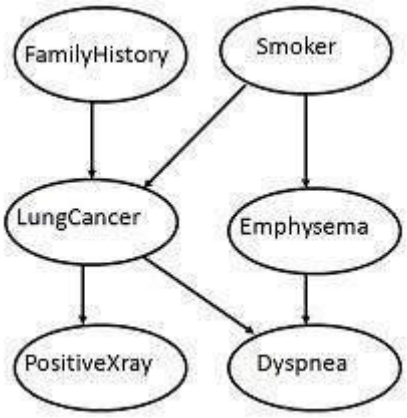
- Directed acyclic graph
- A set of conditional probability tables

Directed Acyclic Graph

- Each node in a directed acyclic graph represents a random variable.
- These variables may be discrete or continuous valued.
- These variables may correspond to the actual attribute given in the data.

Directed Acyclic Graph Representation

The following diagram shows a directed acyclic graph for six Boolean variables.



The arc in the diagram allows representation of causal knowledge. For example, lung cancer is influenced by a person's family history of lung cancer, as well as whether or not the person is a smoker. It is worth noting that the variable PositiveXray is independent of whether the patient has a family history of lung cancer or that the patient is a smoker, given that we know the patient has lung cancer.

Conditional Probability Table

The conditional probability table for the values of the variable LungCancer (LC) showing each possible combination of the values of its parent nodes, FamilyHistory (FH), and Smoker (S) is as follows −

	FH,S	FH,-S	-FH,S	-FH,S
LC	0.8	0.5	0.7	0.1
-LC	0.2	0.5	0.3	0.9

Rule Based Classification

IF-THEN Rules

Rule-based classifier makes use of a set of IF-THEN rules for classification. We can express a rule in the following from −

IF condition THEN conclusion

Let us consider a rule R1,

R1: IF age = youth AND student = yes THEN buy_computer = yes

Points to remember –

- The IF part of the rule is called **rule antecedent** or **precondition**.
- The THEN part of the rule is called **rule consequent**.
- The antecedent part the condition consist of one or more attribute tests and these tests are logically ANDed.
- The consequent part consists of class prediction.

Note − We can also write rule R1 as follows −

R1: (age = youth) ^ (student = yes))(buys computer = yes)

If the condition holds true for a given tuple, then the antecedent is satisfied.

Rule Extraction

Here we will learn how to build a rule-based classifier by extracting IF-THEN rules from a decision tree.

Points to remember –

To extract a rule from a decision tree −

- One rule is created for each path from the root to the leaf node.
- To form a rule antecedent, each splitting criterion is logically ANDed.
- The leaf node holds the class prediction, forming the rule consequent.

Types of data

At the highest level, two kinds of data exist: ***quantitative*** and ***qualitative***.

Quantitative data deals with numbers and things you can measure objectively: dimensions such as height, width, and length, Temperature and humidity, Prices, Area and volume.

Qualitative data deals with characteristics and descriptors that can't be easily measured, but can be observed subjectively—such as smells, tastes, textures, attractiveness, and color.

There are two types of quantitative data, which is also referred to as numeric data: ***continuous*** and ***discrete***. As a general rule, *counts* are discrete and *measurements* are continuous.

Discrete data is a count that can't be made more precise. Typically it involves integers. For instance, the number of children (or adults, or pets) in your family is discrete

data, because you are counting whole, indivisible entities: you can't have 2.5 kids, or 1.3 pets.

Continuous data, on the other hand, could be divided and reduced to finer and finer levels. For example, you can measure the height of your kids at progressively more precise scales—meters, centimeters, millimeters, and beyond—so height is continuous data.

There are three main kinds of qualitative data.

1. Binomial
2. Nominal
3. Ordinal

Binary data place things in one of two mutually exclusive categories: right/wrong, true/false, or accept/reject.

When collecting ***unordered*** or ***nominal*** data, we assign individual items to named categories that do not have an implicit or natural value or rank.

We also can have ***ordered*** or ***ordinal*** data, in which items are assigned to categories that do have some kind of implicit or natural order, such as "Short, Medium, or Tall."

Categorization of Major Clustering Methods

Cluster is a group of objects that belongs to the same class. In other words, similar objects are grouped in one cluster and dissimilar objects are grouped in another cluster. Clustering is the process of making a group of abstract objects into classes of similar objects.

Applications of Cluster Analysis

- Clustering analysis is broadly used in many applications such as market research, pattern recognition, data analysis, and image processing.
- Clustering can also help marketers discover distinct groups in their customer base. And they can characterize their customer groups based on the purchasing patterns.
- In the field of biology, it can be used to derive plant and animal taxonomies, categorize genes with similar functionalities and gain insight into structures inherent to populations.

- Clustering also helps in identification of areas of similar land use in an earth observation database. It also helps in the identification of groups of houses in a city according to house type, value, and geographic location.
- Clustering also helps in classifying documents on the web for information discovery.
- Clustering is also used in outlier detection applications such as detection of credit card fraud.
- As a data mining function, cluster analysis serves as a tool to gain insight into the distribution of data to observe characteristics of each cluster.

Clustering Methods

Clustering methods can be classified into the following categories −

- Partitioning Method
- Hierarchical Method
- Density-based Method
- Grid-Based Method
- Model-Based Method
- Constraint-based Method

Partitioning Method

Suppose we are given a database of 'n' objects and the partitioning method constructs 'k' partition of data. Each partition will represent a cluster and k ≤ n. It means that it will classify the data into k groups, which satisfy the following requirements −

- Each group contains at least one object.
- Each object must belong to exactly one group.

Note −

- For a given number of partitions (say k), the partitioning method will create an initial partitioning.
- Then it uses the iterative relocation technique to improve the partitioning by moving objects from one group to other.

Hierarchical Methods

This method creates a hierarchical decomposition of the given set of data objects. We can classify hierarchical methods on the basis of how the hierarchical decomposition is formed. There are two approaches here −

- Agglomerative Approach
- Divisive Approach

Agglomerative Approach

This approach is also known as the bottom-up approach. In this, we start with each object forming a separate group. It keeps on merging the objects or groups that are close to one another. It keep on doing so until all of the groups are merged into one or until the termination condition holds.

Divisive Approach

This approach is also known as the top-down approach. In this, we start with all of the objects in the same cluster. In the continuous iteration, a cluster is split up into smaller clusters. It is down until each object in one cluster or the termination condition holds. This method is rigid, i.e., once a merging or splitting is done, it can never be undone.

Approaches to Improve Quality of Hierarchical Clustering

Here are the two approaches that are used to improve the quality of hierarchical clustering −

- Perform careful analysis of object linkages at each hierarchical partitioning.
- Integrate hierarchical agglomeration by first using a hierarchical agglomerative algorithm to group objects into micro-clusters, and then performing macro-clustering on the micro-clusters.

Density-based Method

This method is based on the notion of density. The basic idea is to continue growing the given cluster as long as the density in the neighborhood exceeds some threshold, i.e., for each data point within a given cluster, the radius of a given cluster has to contain at least a minimum number of points.

Grid-based Method

In this, the objects together form a grid. The object space is quantized into finite number of cells that form a grid structure.

Advantages

- The major advantage of this method is fast processing time.
- It is dependent only on the number of cells in each dimension in the quantized space.

Model-based methods

In this method, a model is hypothesized for each cluster to find the best fit of data for a given model. This method locates the clusters by clustering the density function. It reflects spatial distribution of the data points.

This method also provides a way to automatically determine the number of clusters based on standard statistics, taking outlier or noise into account. It therefore yields robust clustering methods.

Constraint-based Method

In this method, the clustering is performed by the incorporation of user or application-oriented constraints. A constraint refers to the user expectation or the properties of desired clustering results. Constraints provide us with an interactive way of communication with the clustering process. Constraints can be specified by the user or the application requirement.

Outlier Analysis

It is one of the Data mining function or process. Outliers may be defined as following:

- A database may contain data objects that do not comply with the general behavior or
- Model of the data. Such data objects, which are grossly different from or inconsistent with the remaining set of data, are called outliers.
- Most data mining methods discard outliers as noise or exceptions.
- However, in some applications such as fraud detection, the rare events can be more interesting than the more regularly occurring ones.
- The analysis of outlier data is referred to as outlier mining.
- Outliers may be detected using statistical tests that assume a distribution or probability model for the data, or using distance measures where objects that are a substantial distance from any other cluster are considered outliers.
- Rather than using statistical or distance measures, deviation-based methods identify outliers by examining differences in the main characteristics of objects in a group.
- Outliers can be caused by measurement or execution error.
- Outliers may be the result of inherent data variability.

- Many data mining algorithms try to minimize the influence of outliers or eliminate them all together.
- This, however, could result in the loss of important hidden information because one person's noise could be another person's signal.
- Thus, outlier detection and analysis is an interesting data mining task, referred to as outlier mining.

Data Mining Applications

Data mining is widely used in diverse areas. There are a number of commercial data mining systems available today and yet there are many challenges in this field. In this tutorial, we will discuss the applications and the trend of data mining.

Here is the list of areas where data mining is widely used −

- Financial Data Analysis
- Retail Industry
- Telecommunication Industry
- Biological Data Analysis
- Other Scientific Applications
- Intrusion Detection

Financial Data Analysis

The financial data in banking and financial industry is generally reliable and of high quality which facilitates systematic data analysis and data mining. Some of the typical cases are as follows −

- Design and construction of data warehouses for multidimensional data analysis and data mining.
- Loan payment prediction and customer credit policy analysis.
- Classification and clustering of customers for targeted marketing.
- Detection of money laundering and other financial crimes.

Retail Industry

Data Mining has its great application in Retail Industry because it collects large amount of data from on sales, customer purchasing history, goods transportation, consumption and services. It is natural that the quantity of data collected will continue to expand rapidly because of the increasing ease, availability and popularity of the web.

Data mining in retail industry helps in identifying customer buying patterns and trends that lead to improved quality of customer service and good customer retention and satisfaction. Here is the list of examples of data mining in the retail industry −

- Design and Construction of data warehouses based on the benefits of data mining.
- Multidimensional analysis of sales, customers, products, time and region.
- Analysis of effectiveness of sales campaigns.
- Customer Retention.
- Product recommendation and cross-referencing of items.

Telecommunication Industry

Today the telecommunication industry is one of the most emerging industries providing various services such as fax, pager, cellular phone, internet messenger, images, e-mail, web data transmission, etc. Due to the development of new computer and communication technologies, the telecommunication industry is rapidly expanding. This is the reason why data mining is become very important to help and understand the business.

Data mining in telecommunication industry helps in identifying the telecommunication patterns, catch fraudulent activities, make better use of resource, and improve quality of service. Here is the list of examples for which data mining improves telecommunication services −

- Multidimensional Analysis of Telecommunication data.
- Fraudulent pattern analysis.
- Identification of unusual patterns.
- Multidimensional association and sequential patterns analysis.
- Mobile Telecommunication services.
- Use of visualization tools in telecommunication data analysis.

Biological Data Analysis

In recent times, we have seen a tremendous growth in the field of biology such as genomics, proteomics, functional Genomics and biomedical research. Biological data mining is a very important part of Bioinformatics. Following are the aspects in which data mining contributes for biological data analysis −

- Semantic integration of heterogeneous, distributed genomic and proteomic databases.
- Alignment, indexing, similarity search and comparative analysis multiple nucleotide sequences.
- Discovery of structural patterns and analysis of genetic networks and protein pathways.
- Association and path analysis.
- Visualization tools in genetic data analysis.

Other Scientific Applications

The applications discussed above tend to handle relatively small and homogeneous data sets for which the statistical techniques are appropriate. Huge amount of data have been collected from scientific domains such as geosciences, astronomy, etc. A large amount of data sets is being generated because of the fast numerical simulations in various fields such as climate and ecosystem modeling, chemical engineering, fluid dynamics, etc. Following are the applications of data mining in the field of Scientific Applications −

- Data Warehouses and data preprocessing.
- Graph-based mining.
- Visualization and domain specific knowledge.

Intrusion Detection

Intrusion refers to any kind of action that threatens integrity, confidentiality, or the availability of network resources. In this world of connectivity, security has become the major issue. With increased usage of internet and availability of the tools and tricks for intruding and attacking network prompted intrusion detection to become a critical component of network administration. Here is the list of areas in which data mining technology may be applied for intrusion detection −

- Development of data mining algorithm for intrusion detection.
- Association and correlation analysis, aggregation to help select and build discriminating attributes.
- Analysis of Stream data.
- Distributed data mining.
- Visualization and query tools.