CSC 510: COMPUTER MODELLING AND SIMULATION

MODULE 1: Computer Models: A computer model is a representation of a real-life system or situation. The real-life situation could be for example: the workings of a nuclear reactor or the evacuation of a football stadium. A collection of rules is created to study what would happen in real-life situations. Changes are made to see how they affect the outcome.

Modelling is the process of representing a model which includes its construction and working. This model is similar to a real system, which helps the analyst predict the effect of changes to the system. In other words, modelling is creating a model which represents a system including their properties. It is an act of building 'a model.

Simulation of a system is the operation of a model in terms of time or space, which helps analyze the performance of an existing or a proposed system. In other words, simulation is the process of using a model to study the performance of a system. It is an act of using a model for simulation.

Modelling & Simulation ─ Advantages

Following are the advantages of using Modelling and Simulation −

- **Easy to understand** − Allows to understand how the system really operates without working on real-time systems.
- **Easy to test** − Allows to make changes into the system and their effect on the output without working on real-time systems.
- **Easy to upgrade** − Allows to determine the system requirements by applying different configurations.
- **Easy to identifying constraints** − Allows to perform bottleneck analysis that causes delay in the work process, information, etc.
- **Easy to diagnose problems** − Certain systems are so complex that it is not easy to understand their interaction at a time. However, Modelling & Simulation allows to understand all the interactions and analyze their effect. Additionally, new policies, operations, and procedures can be explored without affecting the real system.

Modelling & Simulation ─ Disadvantages

Following are the disadvantages of using Modelling and Simulation −

- Designing a model is an art which requires domain knowledge, training and experience.
- Operations are performed on the system using random number, hence difficult to predict the result.
- Simulation requires manpower and it is a time-consuming process.
- Simulation results are difficult to translate. It requires experts to understand.
- Simulation process is expensive.

Softwares for Modeling and Simulation:

SIMULIA from Dassault Systemes is a simulation application for 3d objects.
MATLAB - a programming, modeling and simulation tool developed by MathWorks.
SIMUL8 - software for discrete event or process based simulation.
RoboLogix - robotics simulation software developed by Logic Design Inc.
AnyLogic - a multi-method simulation modeling tool for business and science. Developed by The AnyLogic Company.
ADINA - engineering simulation software for structural, fluid, heat transfer, and multiphysics problems.
MapleSim - a multi-domain modeling and simulation tool developed by Waterloo Maple Inc.
Mathematica - a computational software program based on symbolic mathematics, developed by Wolfram Research.
Maple - a general-purpose computer algebra system developed and sold commercially by Waterloo Maple Inc.
DX Studio - a suite of tools for simulation and visualization.
APMonitor - a tool for dynamic simulation, validation, and optimization of multi-domain systems with interfaces to Python and MATLAB.

MODULE 2: DECISION-MAKING UNDER CERTAINTY, RISK AND UNCERTAINTY

A decision is a choice between two or more courses of action. Decision making under uncertainty is the act of choosing between two or more courses of action when the outcomes of those actions are uncertain.

A condition of certainty exists when the decision-maker knows with reasonable certainty what the alternatives are, what conditions are associated with each alternative, and the outcome of each alternative. Under conditions of certainty, accurate, measurable, and reliable information on which to base decisions is available.

The cause and effect relationships are known and the future is highly predictable under conditions of certainty. Such conditions exist in case of routine and repetitive decisions concerning the day-to-day operations of the business.

Decision-making under Risk:

When a manager lacks perfect information or whenever an information asymmetry exists, risk arises. Under a state of risk, the decision maker has incomplete information about available alternatives but has a good idea of the probability of outcomes for each alternative.

While making decisions under a state of risk, managers must determine the probability associated with each alternative on the basis of the available information and his experience.

Decision-making under Uncertainty

What is uncertainty and what are the types of uncertainty?

Uncertainty is a lack of knowledge. Among the various fields that are concerned with uncertainty, there is no common agreement on the terminology, definition, or classification of uncertainty. Several useful typologies exist. Typologies are intellectual constructs; there-fore, it is appropriate to choose the typology that is most useful given the purpose of the work. This report adopts a typology that has been widely used and has proven to be a useful way of thinking about uncertainty in the context of quantitative analysis. Uncertainty can be classified either as **input uncertainty or model uncertainty.**

Input uncertainty arises from a lack of knowledge about the true value of quantities used in analyzing a decision. Often, these quantities are found in scientific models that are used to support a decision, such as hydrologic and environmental models. Model uncertainty is uncertainty about the form of the model used to support the decision. In other words, model uncertainty is uncertainty about what variables, assumptions, and functions best characterize the processes being modeled. In practice, model uncertainties are much more difficult to deal with than input uncertainties because they require the analyst to propose and evaluate competing models.

Most significant decisions made in today's complex environment are formulated under a state of uncertainty. Conditions of uncertainty exist when the future environment is unpredictable and everything is in a state of flux. The decision-maker is not aware of all available alternatives, the risks associated with each, and the consequences of each alternative or their probabilities.

The decision maker does not possess complete information about the alternatives and whatever information is available, may not be completely reliable. In the face of such uncertainty, there is the need to make certain assumptions about the situation in order to provide a reasonable framework for decision-making. So, there is a dependant on judgment and experience for making decisions.

Modern Approaches to Decision-making under Uncertainty:

There are several modern techniques to improve the quality of decision-making under conditions of uncertainty.

(1) Risk analysis,

(2) Preference theory.

(3) Decision trees

Risk Analysis:

Managers who follow this approach analyze the size and nature of the risk involved in choosing a particular course of action.

For instance, while launching a new product, a manager has to carefully analyze each of the following variables the cost of launching the product, its production cost, the capital investment required, the price that can be set for the product, the potential market size and what percent of the total market it will represent.

Risk analysis involves quantitative and qualitative risk assessment, risk management and risk communication and provides managers with a better understanding of the risk and the benefits associated with a proposed course of action. The decision represents a trade-off between the risks and the benefits associated with a particular course of action under conditions of uncertainty.

Preference or Utility Theory: This is another approach to decision-making under conditions of uncertainty. This approach is based on the notion that individual attitudes towards risk vary. Some individuals are willing to take only smaller risks ("risk averters"), while others are willing to take greater risks ("gamblers"). Statistical probabilities associated with the various courses of action are based on the assumption that decision-makers will follow them.

For instance, if there were a 60 percent chance of a decision being right, it might seem reasonable that a person would take the risk. This may not be necessarily true as the individual might not wish to take the risk, since the chances of the decision being wrong are 40 percent. The attitudes towards risk vary with events, with people and positions.

Top-level managers usually take the largest amount of risk. However, the same managers who make a decision that risks millions of rupees of the company in a given program with a 75 percent chance of success are not likely to do the same with their own money.

Moreover, a manager willing to take a 75 percent risk in one situation may not be willing to do so in another. Similarly, a top executive might launch an advertising campaign having a 70 percent chance of success but might decide against investing in plant and machinery unless it involves a higher probability of success.

Though personal attitudes towards risk vary, two things are certain.

Firstly, attitudes towards risk vary with situations, i.e. some people are risk averters in some situations and gamblers in others.

Secondly, some people have a high aversion to risk, while others have a low aversion.

Decision Trees: These are considered to be one of the best ways to analyze a decision. A decision-tree approach involves a graphic representation of alternative courses of action and the possible outcomes and risks associated with each action. By means of a “tree” diagram depicting the decision points, chance events and probabilities involved in various courses of action. This technique of decision-making allows the decision-maker to trace the optimum path or course of action.

Decision trees are schematic representations of the question of interest and the possible consequences that occur from following each strategy.

In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.

- In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.
- The decisions or the test are performed on the basis of features of the given dataset.
- *It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions.*
- It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure.
- In order to build a tree, we use the CART algorithm, which stands for Classification and Regression Tree algorithm.
- A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.

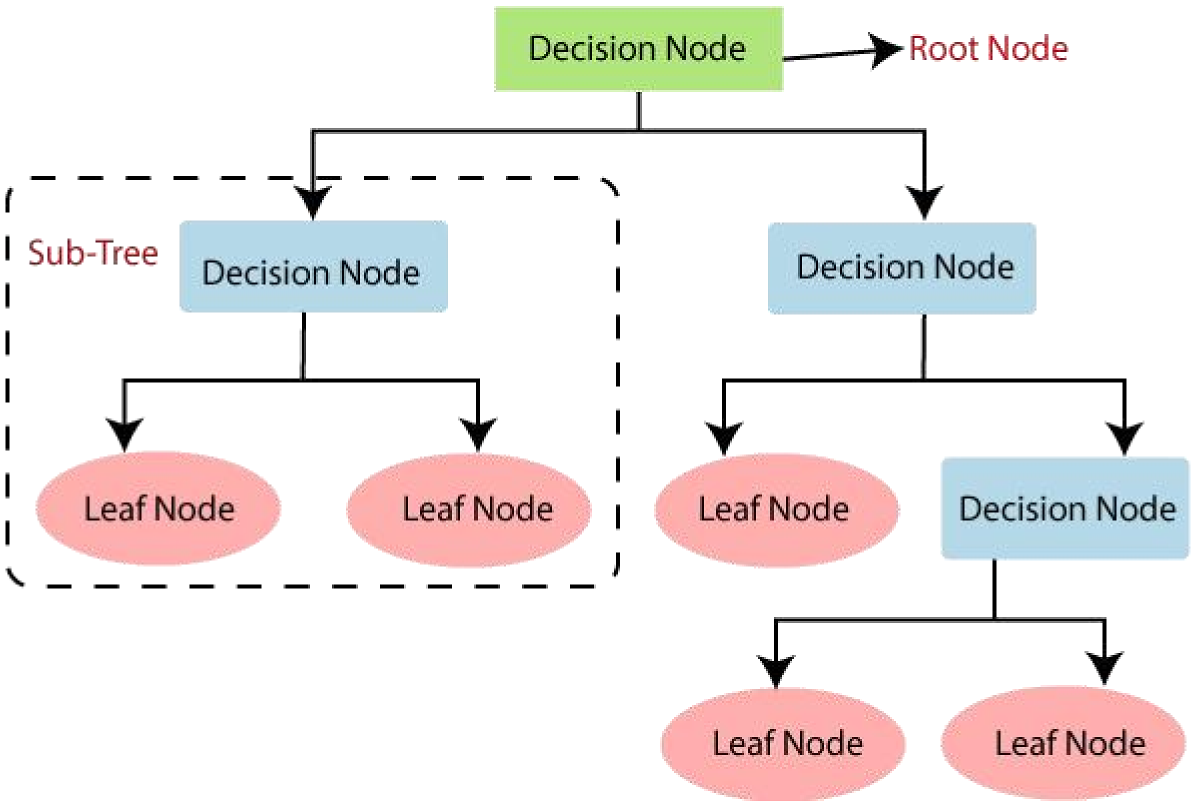


Figure 1: The Decision tree

Reasons for using the Decision tree include:

- Decision Trees usually mimic human thinking ability while making a decision, so it is easy to understand.
- The logic behind the decision tree can be easily understood because it shows a tree-like structure.

Decision Tree Terminologies

Root Node: Root node is from where the decision tree starts. It represents the entire dataset, which further gets divided into two or more homogeneous sets.

Leaf Node: Leaf nodes are the final output node, and the tree cannot be segregated further after getting a leaf node.

Splitting: Splitting is the process of dividing the decision node/root node into sub-nodes according to the given conditions.

Branch/Sub Tree: A tree formed by splitting the tree.

Pruning: Pruning is the process of removing the unwanted branches from the tree.

Parent/Child node: The root node of the tree is called the parent node, and other nodes are called the child nodes.

How the Decision Tree algorithm Work

In a decision tree, for predicting the class of the given dataset, the algorithm starts from the root node of the tree. This algorithm compares the values of root attribute with the record (real dataset) attribute and, based on the comparison, follows the branch and jumps to the next node. For the next node, the algorithm again compares the attribute value with the other sub-nodes and move further. It continues the process until it reaches the leaf node of the tree. The complete process can be better understood using the below algorithm:

Step-1: Begin the tree with the root node, says S, which contains the complete dataset

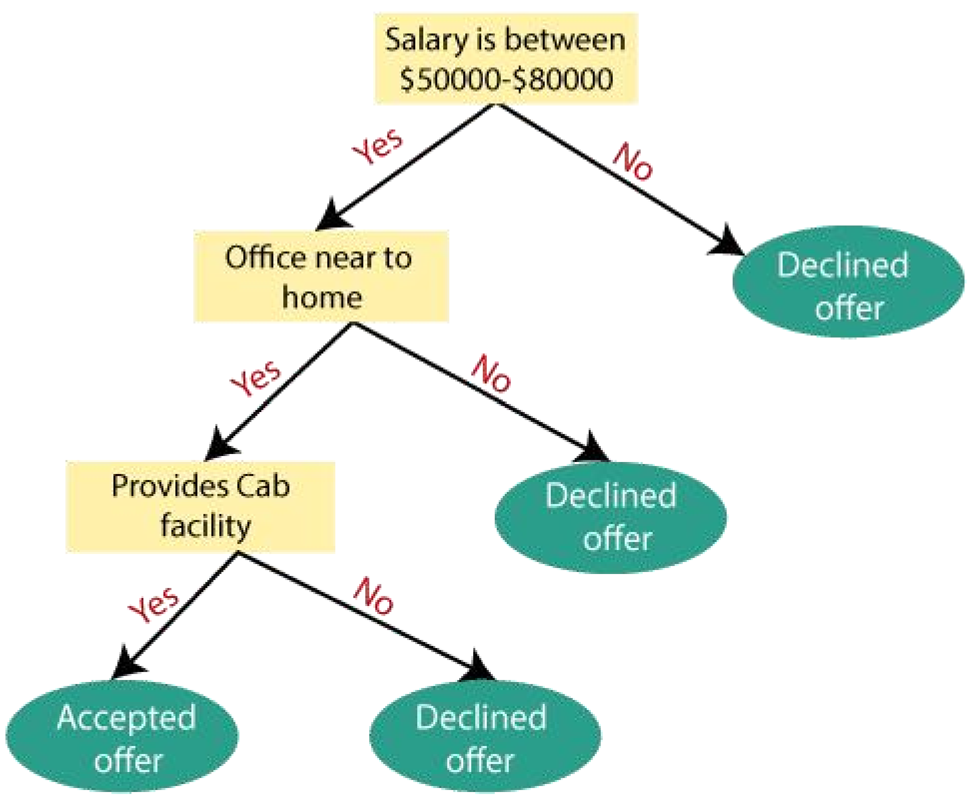
.Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).

Step-3: Divide the S into subsets that contains possible values for the best attributes.

Step-4: Generate the decision tree node, which contains the best attribute.

Step-5: Recursively make new decision trees using the subsets of the dataset created in step - 3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Example: Suppose there is a candidate who has a job offer and wants to decide whether he should accept the offer or Not. So, to solve this problem, the decision tree starts with the root node (Salary attribute by ASM). The root node splits further into the next decision node (distance from the office) and one leaf node based on the corresponding labels. The next decision node further gets split into one decision node (Cab facility) and one leaf node. Finally, the decision node splits into two leaf nodes (Accepted offers and Declined offer). Consider the below diagram:



Attribute Selection Measures

While implementing a Decision tree, the main issue arises that how to select the best attribute for the root node and for sub-nodes. So, to solve such problems there is a technique which is called as Attribute selection measure or ASM. By this measurement, we can easily select the best attribute for the nodes of the tree.

Pruning: Getting an Optimal Decision tree

Pruning is a process of deleting the unnecessary nodes from a tree in order to get the optimal decision tree.

A too-large tree increases the risk of overfitting, and a small tree may not capture all the important features of the dataset. Therefore, a technique that decreases the size of the learning tree without reducing accuracy is known as Pruning. There are mainly two types of tree pruning technology used:

- Cost Complexity Pruning
- Reduced Error Pruning.

Advantages of the Decision Tree

- It is simple to understand as it follows the same process which a human follow while making any decision in real-life.
- It can be very useful for solving decision-related problems.

- It helps to think about all the possible outcomes for a problem.
- There is less requirement of data cleaning compared to other algorithms.

Disadvantages of the Decision Tree

- The decision tree contains lots of layers, which makes it complex.

It may have an overfitting issue, which can be resolved using the Random Forest algorithm.

MODULE 3: MAXIMUM AND MINIMUM REGRET RULES : The Maximax (Optimistic):The Maximax approach otherwise known as the Optimistic seeks the largest of the maximum payoffs among alternatives. It looks at the best possible results. Maximax means maximise the maximum profit.

Economy

Alternatives	Growing	Stable	Declining
Bonds	40	45	5
Stocks	70	30	-13
Mutual Funds	53	45	-5

Table 1: Payoff Table

Looking at the Payoff Table above,

The best for Bonds is 45.

The best for Stocks is 70.

And the best for Mutual Funds is 53.

The overall best is 70, therefore the decision is to invest in **Stocks**. (ie maximizing the maximum payoff)

The Maximin(Conservative or Pessimistic): seeks the largest of the minimum payoffs among actions. The maximin decision rule suggests that a decision maker should select the alternative that offers the least unattractive worst outcome. This would mean choosing the alternative that maximise the minimum profits.

Illustrating the Maximin approach with the above stable, Worst for *Bonds* is 5, for *Stocks* is -13 and *Mutual Funds* is -5. So choosing the alternative with the best of the worst payoff, the pessimistic or conservative approach is to invest in **Bonds.**

The Minimax Regret criterion: seeks the smallest of the maximum regrets among the decisions.Under this Minimax Regret Criterion, the decision maker calculates the maximum opportunity loss values (or also known as regret) for each alternative, and then she chooses the decision that has the lowest maximum regret.

The regret or opportunity loss for a specific alternative, at a given state of nature, is how much we lose by choosing that alternative and not the optimal alternative, given that state of nature (if the current alternative IS the optima alternative, then the opportunity loss for that alternative, given the state of nature, is 0).

Regret (**Opportunity loss**) = Best Payoff – Payoff Received in a particular state of Nature.

Using the above formula to determine the regret for each alternatives, we have:

For Growing Economy, the best payoff is to subtract each payoff received in the growing state from 70 (Best payoff for growing economy).

Bonds under growing : 70-40 = 30

Stocks under growing: 70-70 = 0

Mutual Funds under growing:70-53 =17

For Stable Economy,

Bonds: 45-45 = 0 etc

Do the same for each of the following each of the column using the above formula.

Alternatives	Growing	Stable	Declining
Bonds	70-40 = 30 40	45-45 =0 45	5-5 = 0 5
Stocks	70-70 = 0 70	45-30 = 15 30	5-(-13) =18 -13
Mutual Funds	70-53 =17 53	45-45 = 0 45	5-(-5) = 10 -5

So our new table will be:

Alternatives	Growing	Stable	Declining
Bonds	30	0	0
Stocks	0	15	18

Mutual Funds	17	0	10

Looking at the table, For Bonds, Maximum regret is 30, 18 for Stocks and 17 for Mutual Funds.

The minimum of the maximum regrets is 17. So, the decision is to invest in **Mutual Funds.**

MODULE 4: INVENTORY AND SCHEDULING SYSTEMS: An inventory System is a technology solution used to integrate all information regarding stock levels and stock movement for an organization. It is the process by which you tracks are kept throughout your entire supply chain, from purchasing to production to end sales. It governs how you approach inventory management for your stocks.

Example: Perform the Simulation of the following Inventory Systems given daily demand as represented by the random numbers; 4, 3, 8, 2, 5.

The demand probability given as:

Demand	0	1	2
Probability	0.2	0.5	0.3

Solution:

Table of Cumulative Probability (CP) & Random Digit Assignment (RDA)

Demand	**Probability**	**(CP)**	**(RDA)**
0	0.2	0.2+0=0.2	1-2
1	0.5	0.2+0.5=0.7	3-7
2	0.3	0.7+0.3=1.0	8-0

Note: The CP must end in 1, if not go back and check where you got it wrong.

Thus, the Daily Simulation Table

Days	**Begin Inventory**	**Random Demand**	**Demand**	**End Inventory**	**Shortage**
1	4	4	1	3	0
2	3	3	1	2	0
3	2	8	2	0	0
4	0	2	0	0	0
5	0	5	1	0	1

From the final Simulation, it can be seen that a shortage of 1 occurred at the 5th day. This is the natural extension to attempt to apply simulation on a day- to–day basis to predict schedule performance in a bit to adjust before the real world challenges occur. Simulation model plays through schedules thereby providing performance information.

MODULE 5:TME SERIES ANALYSIS/FORECASTING

Time Series Analysis: Time series essentially is a series of quantitative values. These values are obtained over time, and often have equal time intervals between them. These intervals can be quite different and may consist of yearly, quarterly, monthly or hourly buckets for instance. Time series data is data that is collected at different points in time. This is opposed to cross-sectional data which observes individuals, companies, etc. at a single point in time. Because data points in time series are collected at adjacent time periods there is potential for correlation between observations. This is one of the features that distinguishes time series data from cross-sectional data. A proper time series however does provide an important contribution to a more accurate forecasting. The availability of the right time series makes all the difference. Two or more years of data should normally suffice as a rule of thumb. More data does not necessarily equate to better or the right input. When assessing and forecasting the hourly inbound call volume for a call center for example, a proper forecast may rely on 'only' 3 to 4 weeks of data. The more specific the time series, the better any forecast generally would be. The demand of one of your products and the exchange rate of the British Pound Sterling vs the American Dollar is an example of time series. Data points taken over time as a time series analysis may have an internal structure that should be accounted for. This internal structure may be an auto correlation, trend or seasonal variation.

Time Series Model

The use of time series models is twofold:

1. Get an understanding of the factors and structure that produced the observed data
2. Fit a model and proceed to forecasting, monitoring or even feedback and feed forward control.

Time series models may also be split into univariate time series models and multivariate time series models. Univariate time series models are models used when the dependent variable is a single time series. Trying to model an individual's heart rate per minute using only past observations of heart rate and exogenous variables is an example of a univariate time series model.

Multivariate time series models are used when there are multiple dependent variables. In addition to depending on their own past values, each series may depend on past and present values of the other series. Modeling U.S. gross domestic product, inflation, and unemployment together as endogenous variables is an example of a multivariate time series model.

The statistical characteristics of time series data often violate the assumptions of conventional statistical methods. Because of this, analyzing time series data requires a unique set of tools and methods, collectively known as time series analysis.

Time Series analysis is therefore a specific way of analyzing a sequence of datapoints collected over an interval of time. Time Series Analysis is used for many applications such as: Economic Forecasting, Sales Forecasting, Budgetary Analysis, Stock Market Analysis, Yield Projections, Inventory assessments, Workload projections, Weather patterns and forecasts. Time series analyses can provide better insights for business decisions in not just inventory control but also in purchasing, manufacturing, logistics and more.

The relevance of time Series Analysis to Organizations: Time series analysis helps organizations understand the underlying causes of trends or systemic patterns over time. Using data visualizations, business users can see seasonal trends and dig deeper into why these trends occur. With modern analytics platforms, these visualizations can go far beyond line graphs. When organizations analyze data over consistent intervals, they can also use time series forecasting to predict the likelihood of future events. Time series forecasting is part of predictive analytics. It can show likely changes in the data, like seasonality or cyclic behavior, which provides a better understanding of data variables and helps forecast better. Today's technology allows us to collect massive amounts of data every day and it's easier than ever to gather enough consistent data for comprehensive analysis.

Time series analysis is used for non-stationary data—things that are constantly fluctuating over time or are affected by time. Industries like finance, retail, and economics frequently use time series analysis because currency and sales are always changing. Stock market analysis is an excellent example of time series analysis in action, especially with automated trading algorithms. Likewise, time series analysis is ideal for forecasting weather changes, helping meteorologists predict everything from tomorrow's weather report to future years of climate change. Because time series analysis includes many categories or variations of data, analysts sometimes must make complex models. However, analysts can't account for all variances, and they can't generalize a specific model to every sample. Models that are too complex or that try to do too many things can lead to lack of fit. Lack of fit or overfitting models lead to those models not distinguishing between random error and true relationships, leaving analysis skewed and forecasts incorrect.

From time series analysis to time series forecasting: It's often easier and more accurate to forecast for a shorter time horizon compared to a longer horizon. The further the point in time the less accurate forecasts usually get. If you want, you can frequently update your statistical model as you gain more new information that may help to make more accurate forecasts. The use of time series analysis is a helpful instrument in forecasting. Mere time series analysis crunch time series data in order to extract meaningful statistics and other elements of the data. Time series forecasting goes beyond 'just' time series analysis. With time series forecasting a model is being used to predict future values based on previously observed values over time. For as long as we have been recording data, time has been a crucial factor. In time series analysis, time is a significant variable of the data. Times series analysis helps us study our world and learn how we progress within it. Time series analysis is a specific way of analyzing a sequence of data points collected over an interval of time. In time series analysis, analysts record data points at consistent intervals over a set period of time rather than just recording the data points intermittently or randomly. However, this type of analysis is not merely the act of collecting data over time. What sets time series data apart from other data is that the analysis can show how variables change over time. In other words, time is a crucial variable because it shows how the data adjusts over the course of the data points as well as the final results. It provides an additional source of information and a set order of dependencies between the data. Time series analysis typically requires a large number of data points to ensure consistency and reliability. An extensive data set ensures you have a representative sample size and that analysis can cut through noisy data. It also ensures that any trends or patterns discovered are not outliers and can account for seasonal variance. Additionally, time series data can be used for forecasting—predicting future data based on historical data.

Forecasting is a common statistical task in business, where it helps to inform decisions about the scheduling of production, transportation and personnel, and provides a guide to long-term strategic planning. However, business forecasting is often done poorly, and is frequently confused with planning and goals. They are three different things.

Forecasting is about predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact the forecasts.

Goals are what you would like to have happen. Goals should be linked to forecasts and plans, but this does not always occur. Too often, goals are set without any plan for how to achieve them, and no forecasts for whether they are realistic.

Planning is a response to forecasts and goals. Planning involves determining the appropriate actions that are required to make your forecasts match your goals.
Forecasting should be an integral part of the decision-making activities of management, as it can play an important role in many areas of a company. Modern organisations require short-term, medium-term and long-term forecasts, depending on the specific application.

Short-term forecasts are needed for the scheduling of personnel, production and transportation. As part of the scheduling process, forecasts of demand are often also required.

Medium-term forecasts are needed to determine future resource requirements, in order to purchase raw materials, hire personnel, or buy machinery and equipment.

Long-term forecasts are used in strategic planning. Such decisions must take account of market opportunities, environmental factors and internal resources.
An organisation needs to develop a forecasting system that involves several approaches to predicting uncertain events. Such forecasting systems require the development of expertise in identifying forecasting problems, applying a range of forecasting methods, selecting appropriate methods for each problem, and evaluating and refining forecasting methods over

time. It is also important to have strong organisational support for the use of formal forecasting methods if they are to be used successfully.

In the early stages of a forecasting project, decisions need to be made about what should be forecast. For example, if forecasts are required for items in a manufacturing environment, it is necessary to ask whether forecasts are needed for:

1. every product line, or for groups of products?
2. every sales outlet, or for outlets grouped by region, or only for total sales?
3. weekly data, monthly data or annual data?

It is also necessary to consider the forecasting horizon. Will forecasts be required for one month in advance, for 6 months, or for ten years? Different types of models will be necessary, depending on what forecast horizon is most important.

How frequently are forecasts required? Forecasts that need to be produced frequently are better done using an automated system than with methods that require careful manual work.

It is worth spending time talking to the people who will use the forecasts to ensure that you understand their needs, and how the forecasts are to be used, before embarking on extensive work in producing the forecasts.

Once it has been determined what forecasts are required, it is then necessary to find or collect the data on which the forecasts will be based. The data required for forecasting may already exist. These days, a lot of data are recorded, and the forecaster's task is often to identify where and how the required data are stored. The data may include sales records of a company, the historical demand for a product, or the unemployment rate for a geographic region. A large part of a forecaster's time can be spent in locating and collating the available data prior to developing suitable forecasting methods.

Forecasting Data and Methods

The appropriate forecasting methods depend largely on what data are available.

If there are no data available, or if the data available are not relevant to the forecasts, then qualitative forecasting methods must be used. These methods are not purely guesswork—there are well-developed structured approaches to obtaining good forecasts without using historical data.

Quantitative forecasting can be applied when two conditions are satisfied:

1. numerical information about the past is available;
2. it is reasonable to assume that some aspects of the past patterns will continue into the future.

There is a wide range of quantitative forecasting methods, often developed within specific disciplines for specific purposes. Each method has its own properties, accuracies, and costs that must be considered when choosing a specific method.

Most quantitative prediction problems use either time series data (collected at regular intervals over time) or cross-sectional data (collected at a single point in time). In this book we are concerned with forecasting future data, and we concentrate on the time series domain.

Time series forecasting

Examples of time series data include:

- Daily IBM stock prices
- Monthly rainfall
- Quarterly sales results for Amazon
- Annual Google profits

Anything that is observed sequentially over time is a time series. It can be time series that are observed at regular intervals of time (e.g., hourly, daily, weekly, monthly, quarterly, annually). Irregularly spaced time series can also occur, but are beyond the scope of this book.

When forecasting time series data, the aim is to estimate how the sequence of observations will continue into the future.

The simplest time series forecasting methods use only information on the variable to be forecast, and make no attempt to discover the factors that affect its behaviour. Therefore they will extrapolate trend and seasonal patterns, but they ignore all other information such as marketing initiatives, competitor activity, changes in economic conditions, and so on.

Time series models used for forecasting include decomposition models, exponential smoothing models and ARIMA models.

Basic steps in forecasting

A forecasting task usually involves five basic steps.

Step 1: Problem definition: Often this is the most difficult part of forecasting. Defining the problem carefully requires an understanding of the way the forecasts will be used, who requires the forecasts, and how the forecasting function fits within the organisation requiring the forecasts. A forecaster needs to spend time talking to everyone who will be involved in collecting data, maintaining databases, and using the forecasts for future planning.

Step 2: Gathering information: There are always at least two kinds of information required: (a) statistical data, and (b) the accumulated expertise of the people who collect the data and use the forecasts. Often, it will be difficult to obtain enough historical data to be able to fit a good statistical model. In that case, the judgmental forecasting methods can be used. Occasionally, old data will be less useful due to structural changes in the system being forecast; then we may choose to use only the most recent data. However, remember that good statistical models will handle evolutionary changes in the system; don't throw away good data unnecessarily.

Step 3: Preliminary (exploratory) analysis: Always start by graphing the data. Are there consistent patterns? Is there a significant trend? Is seasonality important? Is there evidence of the presence of business cycles? Are there any outliers in the data that need to be explained by those with expert knowledge? How strong are the relationships among the variables available for analysis? Various tools have been developed to help with this analysis.

Step 4: Choosing and fitting models: The best model to use depends on the availability of historical data, the strength of relationships between the forecast variable and any explanatory variables, and the way in which the forecasts are to be used. It is common to compare two or three potential models. Each model is itself an artificial construct that is based on a set of assumptions (explicit and implicit) and usually involves one or more parameters which must be estimated using the known historical data.

Step 5: Using and evaluating a forecasting model. Once a model has been selected and its parameters estimated, the model is used to make forecasts. The performance of the model can only be properly evaluated after the data for the forecast period have become available. A number of methods have been developed to help in assessing the accuracy of forecasts. There are also organisational issues in using and acting on the forecasts. When using a forecasting model in practice, numerous practical issues arise such as how to handle missing values and outliers, or how to deal with short time series.

The Stastistical forecasting perspective

The thing we are trying to forecast is unknown (or we would not be forecasting it), and so we can think of it as a random variable. For example, the total sales for next month could take a range of possible values, and until we add up the actual sales at the end of the month, we don't know what the value will be. So until we know the sales for next month, it is a random quantity.

Simple linear regression is commonly used in forecasting and financial analysis—for a company to tell how a change in the GDP could affect sales. It is a statistical technique for quantifying the relationship between variables. In simple regression analysis, there is one dependent variable (e.g. sales) to be forecast and one independent variable. The values of the independent variable are typically those assumed to "cause" or determine the values of the dependent variable. Thus, if we assume that the amount of advertising dollars spent on a product determines the amount of its sales, we could use regression analysis to quantify the precise nature of the relationship between advertising and sales. For forecasting purposes, knowing the quantified relationship between the variables allows us to provide forecasting estimates.

The simplest regression analysis models the relationship between two variables uisng the following equation:

Y = a + bX

Where

Y is the dependent variable we are trying to forecast

X is the value of our independent variable.

a = the *y* intercept

b= slope of the regression line

Notice that this simple equation denotes a "linear" relationship between X and Y. So this form would be appropriate if, when you plotted a graph of Y and X, you tended to see the points roughly form along a straight line (as compared to having a curvilinear relationship).

When you have several past concurrent observations of Y and X, regression analysis provides a means to calculate the values of a and b, which are assumed to be constant. Since you will then know a and b, if you can provide an estimate of X in some future period, you can calculate a future value of Y from the above equation.