# Certified Business Analytics Professional
# VS-1166

V-Skills Certifications

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# 1. INTRODUCTION

Business analytics (BA) refers to the skills, technologies, practices for exploration and investigation of past business performance to gain insight and drive business planning. Business analytics focuses on developing new insights and understanding of business performance based on data and statistical methods. In contrast, business intelligence traditionally focuses on using a consistent set of metrics to both measure past performance and guide business planning, which is also based on data and statistical methods.

Business analytics makes extensive use of statistical analysis, including explanatory and predictive modeling, and fact-based management to drive decision making. Analytics may be used as input for human decisions or may drive fully automated decisions.

Analytics can be defined as a process that involves the use of statistical techniques (measures of central tendency, graphs, and so on), information system software (data mining, sorting routines), and operations research methodologies (linear programming) to explore, visualize, discover and communicate patterns or trends in data. Simply, analytics convert data into useful information. Analytics is an older term commonly applied to all disciplines, not just business. A typical example of the use of analytics is the weather measurements collected and converted into statistics, which in turn predict weather patterns.

Querying, reporting, OLAP, and alert tools can answer questions such as what happened, how many, how often, where the problem is, and what actions are needed. Business analytics can answer questions like why is this happening, what if these trends continue, what will happen next (or, predict), what is the best that can happen (or, optimize).

Business analytics is the scientific process of transforming data into insight for making better decisions. Business analytics is used for data-driven or fact-based decision making, which is often seen as more objective than other alternatives for decision making.

## 1.1. Evolution and Scope

Analytics have been used in business since the management exercises were put into place by Frederick Winslow Taylor in the late 19th century. Henry Ford measured the time of each component in his newly established assembly line. But analytics began to command more attention in the late 1960s when computers were used in decision support systems. Since then, analytics have changed and formed with the development of enterprise resource planning (ERP) systems, data warehouses, and a large number of other software tools and processes.

In later years the business analytics have exploded with the introduction to computers. This change has brought analytics to a whole new level and has made the possibilities endless. As far as analytics has come in history, and what the current field of analytics is today many people would never think that analytics started in the early 1900s with Mr. Ford himself.

Business Analysis was introduced when Information Technology change projects started to face difficulties in the 1980s. Before that, IT change projects could solve only a limited set of problems in a limited way because the only options were to turn paper based data into electronic data and have simple programs automate the use of that data. A few of the limitations were

- ✓ storage of the electronic data was expensive
- ✓ the way data was stored was cumbersome (flat files read sequentially in one direction only).
- ✓ programs were difficult to write in abstract languages
- ✓ there was only a limited set of functionality based around mainframe processes
- ✓ user interfaces were delivered on basic green-screens

Since the 1980s data storage has become cheaper and covers not just paper based data but audio and visual data too. Other changes that have come about are

- ✓ Relational, object orientated and other databases have made access to data easier
- ✓ Programming languages have evolved in usability and functionality
- ✓ Processing is no longer constrained to mainframes but distributed with increasingly sophisticated user interfaces.

The internet generated a whole new market place and set of business models, as well as a new set of technological possibilities. There are now thousands of 'legacy' systems being upgraded, merged and replaced. The universe of business solutions is an ever expanding one.

The result of all this change was that there are many more choices to make at each stage of an IT and/or any other type of change project. This increases the chances of choosing the wrong method to analyse the project/business. These wrong choices invalidate the subsequent work based on that wrong choice. Going further, the earlier in the project that a wrong choice is made, the greater the damage is in terms of how much re-work is required. With large projects, the inaccurate decisions have larger repercussions.

## Challenges

Business analytics depends on sufficient volumes of high quality data. The difficulty in ensuring data quality is integrating and reconciling data across different systems, and then deciding what subsets of data to make available.

Previously, analytics was considered a type of after-the-fact method of forecasting consumer behavior by examining the number of units sold in the last quarter or the last year. This type of data warehousing required a lot more storage space than it did speed. Now business analytics is becoming a tool that can influence the outcome of customer interactions. When a specific customer type is considering a purchase, an analytics-enabled enterprise can modify the sales pitch to appeal to that consumer. This means the storage space for all that data must react extremely fast to provide the necessary data in real-time.

## Scope

Banks, such as Capital One, use data analysis (or analytics, as it is also called in the business setting), to differentiate among customers based on credit risk, usage and other characteristics and then to match customer characteristics with appropriate product offerings. Harrah's, the gaming firm, uses analytics in its customer loyalty programs. E & J Gallo Winery quantitatively analyzes and predicts the appeal of its wines. Between 2002 and 2005, Deere & Company saved more than

$1 billion by employing a new analytical tool to better optimize inventory. Example : It can help you focus on the fundamental objectives of the business and the ways analytics can serve them. A telecoms company that pursues efficient call centre usage over customer service might save money.

## Relevance

Data analysis is important to businesses will be an understatement. In fact, no business can survive without analyzing available data. Visualize the following situations:

- ✓ A pharma company is performing trials on number of patients to test its new drug to fight cancer. The number of patients under the trial is well over 500.
- ✓ A company wants to launch new variant of its existing line of fruit juice. It wants to carry out the survey analysis and arrive at some meaningful conclusion.
- ✓ Sales director of a company knows that there is something wrong with one of its successful products, however hasn't yet carried out any market research data analysis. How and what does he conclude?

These situations are indicative enough to conclude that data analysis is the lifeline of any business. Whether one wants to arrive at some marketing decisions or fine-tune new product launch strategy, data analysis is the key to all the problems. What is the importance of data analysis - instead, one should say what is not important about data analysis.

Merely analyzing data isn't sufficient from the point of view of making a decision. How does one interpret from the analyzed data is more important. Thus, data analysis is not a decision making system, but decision supporting system.

Data analysis can offer the following benefits

- ✓ Structuring the findings from survey research or other means of data collection
- ✓ Break a macro picture into a micro one
- ✓ Acquiring meaningful insights from the dataset
- ✓ Basing critical decisions from the findings
- ✓ Ruling out human bias through proper statistical treatment

## Types of Analytics

- ✓ Decisive analytics: supports human decisions with visual analytics the user models to reflect reasoning.
- ✓ Descriptive Analytics: Gain insight from historical data with reporting, scorecards, clustering etc.
- ✓ Predictive analytics predictive modeling using statistical and machine learning techniques
- ✓ Prescriptive analytics recommend decisions using optimization, simulation etc.

Analytics is the process of transforming raw data into actionable strategic knowledge in order to gain insight into business processes, and thereby to guide decision-making to help businesses run efficiently. An analytics process can b e categorized into one of three categories:

- ✓ Descriptive Analytics – It looks at an organization's current and historical performance.

- ✓ Predictive Analytics – It forecasts future trends, behavior, and events for decision support.
- ✓ Prescriptive Analytics – It determines alternative courses of actions or decisions, given the current and projected situations and a set of objectives, requirements, and constraints.

## Levels of Analytics

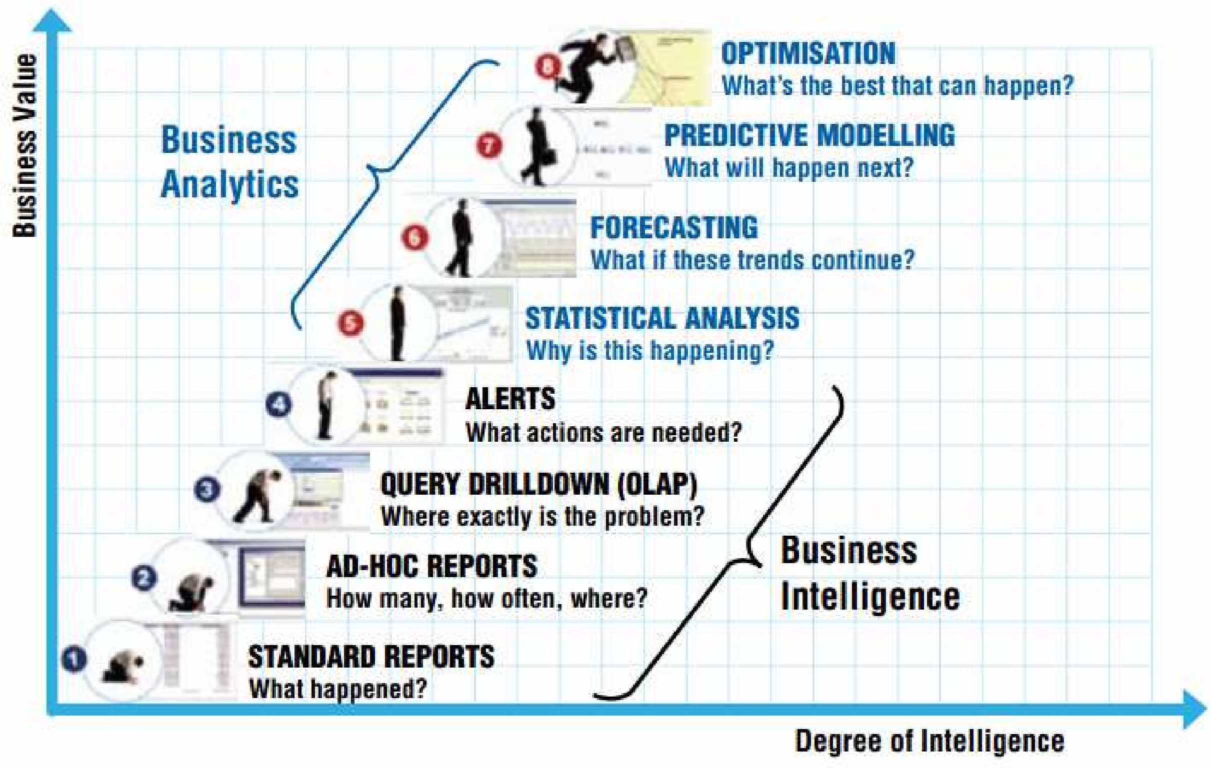
There are an eight levels of "Intelligence through Analytics" which have been outlined by SAS as

- ✓ Standard Reports - The first level of the analytical ladder focuses on understanding what had happened. For example, imagine reviewing a company's annual report and pinpointing the various events that had occurred. "What was sold?", "What was bought?", "What was the volume of fraudulent cases detected?" etc.
- ✓ Ad-Hoc Report - Now that we had understood and captured the events what had happened, secondary questions may surface. Such as, "When did it happen?", "How many times did it occur during a particular period of time?".
- ✓ Query Drilldowns - Online Analytical Processing (OLAP) Diving deeper into the event, answering questions such as, "Where did the event happen?", "Where exactly was the problem?".
- ✓ Alerts - Finally, the concluding stage of the first four levels is alerts. Given the previous three levels, we are keen to act/re-act on the uncovered information by triggering various business specific alerts. What are the actions needed when threshold is breached?

These four levels are common practice in almost all organisations as the foundation of standard business operations. The four levels are known as part of Business Intelligence. That is, the presentation and reporting of historical data. Furthermore, a secondary attribute of Business Intelligence system is that the user knows what they are looking and/or the basic analysis required to produce it. The subsequent levels are where analytical processes kick in.

- ✓ Statistical Analysis - In this level we aim to go beyond the realm of 'what' and 'where', to dive into the hidden gems of the data to understand why , the event had happened. Such knowledge is the foundation of understanding how to identify, prevent, exploit, and so forth.
- ✓ Forecasting - Until this stage we had focused entirely on deriving insight from historical data, one of the key elements of analytics is the capability of statistical forecasting. Will this observed trend continue and for how long? Furthermore, this stage is analogous to driving a car – one needs to have a front windscreen in order to know what is likely to happen.
- ✓ Predictive Modeling - This stage is focused on uncovering the unknown from the data at hand to surface new insights that may not have been previously known, also to provide the foundation for predicting future events, "What will happen next?" and "Why will it happen?", such as the likelihood of events occurring.
- ✓ Optimisation - The cherry on top of the pie, optimisation or also referred to as Operation Research (OR), combines all the previous levels to optimise business processes/objectives given operational and other constraints. How to maximise profit, minimise cost? How to optimally allocate resources?

These four final levels construe Business Analytics, the uncovering of insights from historical data and the projections into future, using analytical processes in alignment to business requirements. To place the full eight levels into a more relatable context, assume the case of customer complaints. The type of questions and insights generated at each of the stages could be the following:




## 1.2. Data for Business Analytics

Data is raw fact, which is collected and analyzed to create information suitable for making decisions. Data is measured, collected and reported, and analyzed, to create information suitable for making decisions.

### Types of data

**Discrete and Continuous**

- ✓ Attribute or discrete data - It is based on counting like the number of processing errors, the count of customer complaints, etc. Discrete data values can only be non-negative integers such as 1, 2, 3, etc. and can be expressed as a proportion or percent (e.g., percent of x, percent good, percent bad). It includes
  - ✓ Count or percentage – It counts of errors or % of output with errors.
  - ✓ Binomial data - Data can have only one of two values like yes/no or pass/fail.
  - ✓ Attribute-Nominal - The "data" are names or labels. Like in a company, Dept A, Dept B, Dept C or in a shop: Machine 1, Machine 2, Machine 3
  - ✓ Attribute-Ordinal - The names or labels represent some value inherent in the object or item (so there is an order to the labels) like on performance - excellent, very good, good, fair, poor or tastes - mild, hot, very hot
- ✓ Variable or continuous data - They are measured on a continuum or scale. Data values for continuous data can be any real number: 2, 3.4691, -14.21, etc. Continuous data can be

recorded at many different points and are typically physical measurements like volume, length, size, width, time, temperature, cost, etc. It is more powerful than attribute as it is more precise due to decimal places which indicate accuracy levels and specificity. It is any variable measured on a continuum or scale that can be infinitely divided.

Data are said to be discrete when they take on only a finite number of points that can be represented by the non-negative integers. An example of discrete data is the number of defects in a sample. Data are said to be continuous when they exist on an interval, or on several intervals. An example of continuous data is the measurement of pH. Quality methods exist based on probability functions for both discrete and continuous data.

Data could easily be presented as variables data like 10 scratches could be reported as total scratch length of 8.37 inches. The ultimate purpose for the data collection and the type of data are the most significant factors in the decision to collect attribute or variables data.

**Cross-sectional and Time series data -** Often financial analysts are interested in particular types of data such as time-series data or cross-sectional data.

- ✓ Time-series data is a set of observations collected at usually discrete and equally spaced time intervals. For example, the daily closing price of a certain stock recorded over the last six weeks is an example of time-series data. Note that a too long or too short time period may lead to time-period bias. Other examples of time-series would be staff numbers at a particular institution taken on a monthly basis in order to assess staff turnover rates, weekly sales figures of ice-cream sold during a holiday period at a seaside resort and the number of students registered for a particular course on a yearly basis. All of the above would be used to forecast likely data patterns in the future.
- ✓ Cross-sectional data - are observations that coming from different individuals or groups at a single point in time. For example, if one considered the closing prices of a group of 20 different tech stocks on December 15, 1986 this would be an example of cross-sectional data. Note that the underlying population should consist of members with similar characteristics. For example, suppose you are interested in how much companies spend on research and development expenses. Firms in some industries such as retail spend little on research and development (R&D), while firms in industries such as technology spend heavily on R&D. Therefore, it's inappropriate to summarize R&D data across all companies. Rather, analysts should summarize R&D data by industry, and then analyze the data in each industry group. Other examples of cross-sectional data would be: an inventory of all ice creams in stock at a particular store, a list of grades obtained by a class of students for a specific test.

**Population and Sample Data**

When we think of the term "population," we usually think of people in our town, region, state or country and their respective characteristics such as gender, age, marital status, ethnic membership, religion and so forth. In statistics the term "population" takes on a slightly different meaning. The "population" in statistics includes all members of a defined group that we are studying or collecting information on for data driven decisions.

A part of the population is called a sample. It is a proportion of the population, a slice of it, a part of it and all its characteristics. A sample is a scientifically drawn group that actually possesses the same characteristics as the population – if it is drawn randomly.(This may be hard for you to believe, but it is true!)

A population includes all of the elements from a set of data. A sample consists of one or more observations from the population.

**Converting Data Types** - Continuous data, tend to be more precise due to decimal places but, need to be converted into discrete data. As continuous data contains more information than discrete data hence, during conversion to discrete data there is loss of information.

Discrete data cannot be converted to continuous data as instead of measuring how much deviation from a standard exists, the user may choose to retain the discrete data as it is easier to use. Converting variable data to attribute data may assist in a quicker assessment, but the risk is that information will be lost when the conversion is made.

**Data Structuring** – It refers to structuring of data elements and is classified as

- ✓ Structured data - Any data that resides in a fixed field within a record or file. This includes data contained in relational databases and spreadsheets. Structured data first depends on creating a data model – a model of the types of business data that will be recorded and how they will be stored, processed and accessed. Structured data has the advantage of being easily entered, stored, queried and analyzed.
- ✓ Semi-structured data - Semi-structured data is a form of structured data that does not conform with the formal structure of data models associated with relational databases or other forms of data tables, but nonetheless contains tags or other markers to separate semantic elements and enforce hierarchies of records and fields within the data. Therefore, it is also known as self-describing structure like XML, JSON
- ✓ Unstructured data - Information that doesn't reside in a traditional row-column database. Examples include e-mail messages, word processing documents, videos, photos, audio files, presentations, web pages and many other kinds of business documents.

## Data collection methods

Data collection is based on crucial aspects of what to know, from whom to know and what to do with the data. Factors which ensure that data is relevant to the project includes

- ✓ Person collecting data like team member, associate, subject matter expert, etc.
- ✓ Type of Data to collect like cost, errors, ratings etc.
- ✓ Time Duration like hourly, daily, batch-wise etc.
- ✓ Data source like reports, observations, surveys etc.
- ✓ Cost of collection

Few types of data collection methods includes

- ✓ Check sheets - It is a structured, well-prepared form for collecting and analyzing data consisting of a list of items and some indication of how often each item occurs. There are several types of check sheets like confirmation check sheets for confirming whether all steps in a process have been completed, process check sheets to record the frequency of observations with a range of measurement, defect check sheets to record the observed frequency of defects and stratified check sheets to record observed frequency of defects by defect type and one other criterion. It is easy to use, provides a choice of observations and good for determining frequency over time. It should be used to collect observable data when the collection is managed by the same person or at the same location from a process.

- ✓ Coded data- It is used when presence of too many digits are to be recorded into small blocks or during data capturing of large sequences of digits from a single observation or rounding off errors are observed whilst recording large digit numbers. It is also used if numeric data is used to represent attribute data or data quantity is not enough for a statistical significance in the sample size. Various types of coded data collection are
  - ✓ Truncation coding for storing only 3,2 or 9 for 1.0003, 1.0002, and 1.0009
  - ✓ Substitution coding – It stores fractional observation, as integers like expressing the number 32 for 32-3/8 inches with 1/8 inch as base.
  - ✓ Category coding - Using a code for category like "S" for scratch
  - ✓ Adding/subtracting a constant or multiplying/dividing by a factor – It is usually used for encoding or decoding
- ✓ Automatic measurements - In it a computer or electronic equipment performs data gathering without human intervention like radioactive level in a nuclear reactor. The equipment observes and records data for analysis and action.

## Data Management

Few important data management related terms are

- ✓ Data quality - It refers to the level of quality of Data. Data is generally considered high quality if, they are fit for their intended uses in operations, decision making and planning.
- ✓ Data cleansing - Data cleaning or data scrubbing is the process of detecting and correcting (or removing) corrupt or inaccurate records from a record set, table, or database. Used mainly in databases, the term refers to identifying incomplete, incorrect, inaccurate, irrelevant, etc. parts of the data and then replacing, modifying, or deleting this dirty data or coarse data.
- ✓ Data validation - It is the process of ensuring that a program operates on clean, correct and useful data. It uses routines, often called "validation rules" "validation constraints" or "check routines", that check for correctness, meaningfulness, and security of data that are input to the system.
- ✓ Data integrity - It refers to maintaining and assuring the accuracy and consistency of data over its entire life-cycle, and is a critical aspect to the design, implementation and usage of any system which stores, processes, or retrieves data.
- ✓ Data governance - It is a control that ensures that the data entry by an operations team member or by an automated process meets precise standards, such as a business rule, a data definition and data integrity constraints in the data model. It is a set of processes that ensures that important data assets are formally managed throughout the enterprise. Data governance ensures that data can be trusted and that people can be made accountable for any adverse event that happens because of low data quality.

## Techniques for Assuring Data Accuracy and Integrity

Data integrity and accuracy have a crucial in the data collection process as they ensure the usefulness of data being collected. Data integrity determines whether the information being measured truly represents the desired attribute and data accuracy determines the degree to which individual or average measurements agree with an accepted standard or reference value.

Data integrity is doubtful if the data collected does not fulfill the purpose like data collected on finished good departure gathers data from truck departures but if the data is recorded on computing device present in the warehouse then integrity is doubtful. Similarly data accuracy is doubtful if the measurement device does not conforms to the laid down device standards.
Bad data can be avoided by following few precautions like avoiding emotional bias relative to tolerances, avoiding unnecessary rounding and screening data to detect and remove data entry errors.

## Digital Data

With change and spread of technology, companies are moving towards digital marketing as consumers are moving towards e-commerce and mobile commerce. Availability of low cost internet access and devices has also spurned this shift amongst consumers. Digital data like html footprints that consumers leave behind when they visit a website or social media data, have significant value over these traditional tools of analytics in multiple ways. To begin with, by analyzing digital data you are 'listening in' to natural, honest conversations that are not limited. It isn't a forced conversation. Second, the sample size is enormous. If you're looking at 2000 consumers in a traditional survey, you're talking about over 200,000 with digital data. Finally, the analysis is less expensive than traditional research, fast and therefore can be conducted multiple times in a year to answer different questions or hypotheses.

## Big Data

Big data is an all-encompassing term for any collection of data sets so large and complex that it becomes difficult to process using on-hand data management tools or traditional data processing applications.

Big data is a large volume unstructured data which can not be handled by standard database management systems like DBMS, RDBMS or ORDBMS. Big Data is very large, loosely structured data set that defies traditional storage. Few examples are as

- ✓ Facebook : has 40 PB of data and captures 100 TB / day
- ✓ Yahoo : 60 PB of data
- ✓ Twitter : 8 TB / day
- ✓ EBay : 40 PB of data, captures 50 TB / day

In defining big data, it's also important to understand the mix of unstructured and multi-structured data that comprises the volume of information.

- ✓ Unstructured data comes from information that is not organized or easily interpreted by traditional databases or data models, and typically, it's text-heavy. Metadata, Twitter tweets, and other social media posts are good examples of unstructured data.
- ✓ Multi-structured data refers to a variety of data formats and types and can be derived from interactions between people and machines, such as web applications or social networks. A great example is web log data, which includes a combination of text and visual images along with structured data like form or transactional information. As digital disruption transforms communication and interaction channels—and as marketers enhance the customer experience

across devices, web properties, face-to-face interactions and social platforms—multi-structured data will continue to evolve.

Big Data is usually characterized by following “V” attributes

- ✓ Volume - Data being handled is so voluminous that it frequently exceeds a server’s storage and processing capacity. When vertical scalable solutions (adding more storage or faster processors) due to costs or zero downtimes are not acceptable options, horizontal scalable solutions (using cheaper servers without shutting down the existing server; for example, using MapReduce Hadoop technology) are needed. Data grows too quickly over time and can overwhelm the capacity and processing power of the existing server. Data may be needed at all times. Cheaper servers are needed for boosting the computational capabilities.
- ✓ Variety - Data from different sources is aggregated i.e. from online, mobile, and social media; and from ubiquitous sensors. The sensors can be at stores and linked devices as part of the Internet of Things (IoT).
- ✓ Veracity It refers to the lack of clarity or certainty. Data is not well-structured relational data such as transactions hence, companies must be able to store any data in a form that can be analyzed
- ✓ Velocity – It refers to the speed needed to analyze and make decisions in tandem to the data being generated. The speed is often measured in fractions of a second as in real-time or how long it takes for a customer to click to leave your site or ignore your location-based mobile offer.

Big data can come from multiple sources, as

- ✓ Web Data -- still it is big data
- ✓ Click stream data - when users navigate a website, the clicks are logged for further analysis (like navigation patterns). Click stream data is important in on line advertising and E-Commerce
- ✓ Sensor Data - sensors embedded in roads to monitor traffic and misc. other applications generate a large volume of data
- ✓ Connected Devices - Smart phones are a great example. For example when you use a navigation application like Google Maps, the phone sends pings back reporting its location and speed (this information is used for calculating traffic hotspots). Just imagine hundreds of millions (or even billions) of devices consuming data and generating data.
- ✓ Social network profiles or Social media data - Sites like Facebook, Twitter, LinkedIn generate a large amount of data. Tapping user profiles from Facebook, LinkedIn, Yahoo, Google, and specific-interest social or travel sites, to cull individuals’ profiles and demographic information, and extend that to capture their hopefully-like-minded networks.
- ✓ Social influencers – Editor, analyst and subject-matter expert blog comments, user forums, Twitter & Facebook “likes,” Yelp-style catalog and review sites, and other review-centric sites like Apple’s App Store, Amazon, etc.
- ✓ Activity-generated data—Computer and mobile device log files, aka “The Internet of Things.” This category includes web site tracking information, application logs, and sensor data – such as check-ins and other location tracking – among other machine-generated content. But consider also the data generated by the processors found within vehicles, video games, cable boxes or, soon, household appliances.

- ✓ Public—Microsoft Azure Market Place/ Data Market, The World Bank, SEC/Edgar, Wikipedia, IMDb, etc. – data that is publicly available on the Web which may enhance the types of analysis able to be performed.

## 1.3. Decision Models

Decision models are used to model a decision being made once as well as to model a repeatable decision-making approach that will be used over and over again. Development of decision model follows in various steps i.e. formulating, evaluating, appraising and refining a model.
The various steps are listed as

- ✓ Formulation - Formulation is the first and often most challenging stage. The objective of the formulation stage is to develop a formal model of the given decision. This may be represented as a network of decision-making elements, as a decision tree or in other ways depending on the specific situation. The formulation may be conceptual or may include all the necessary decision logic (business rules) required to define the decision-making.
- ✓ Evaluation - For a decision being made once, the objective of the evaluation stage is to produce a formal recommendation (and its associated sensitivities) from a formal model of the decision situation. For a repeatable decision evaluation occurs each time the decision is made by applying the decision model that has been developed.
- ✓ Appraisal - The objective of the appraisal stage is for the decision maker to develop insight into the decision and determine a clear course of action. Much of the insight developed in this stage results from exploring the implications of the formal decision model developed during the formulation stage (i.e., from mining the model). Possible actions following the appraisal stage include implementing the recommended course of action, revising the formal model and reevaluating it, or abandoning the analysis and doing something else.
- ✓ Refinement - The refinement stage responds to the insights obtained during the Appraisal stage. Effective refinement activities include opportunities to test possible decision model changes to see their implications and suggest better ways to modify the decision model.

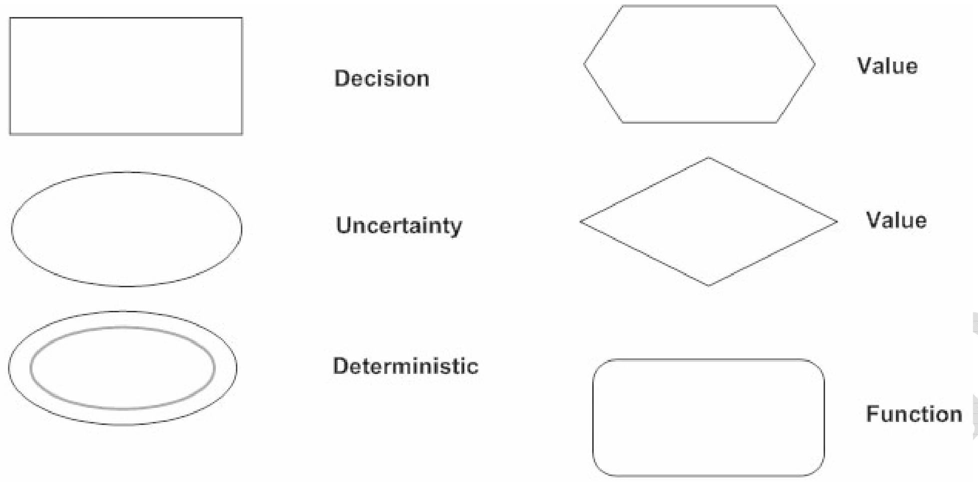
Various approaches for problem solving are used, which includes

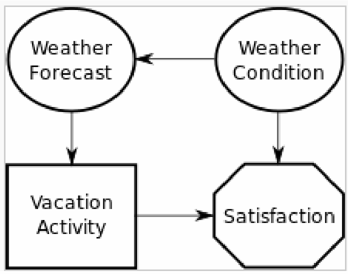
### Graphical models

They graphically depict the various elements of the problem and their relationships as with the usage of influence diagrams. An influence diagram (ID) (also called a relevance diagram, decision diagram or a decision network) is a compact graphical and mathematical representation of a decision situation. It is a generalization of a Bayesian network, in which not only probabilistic inference problems but also decision making problems (following maximum expected utility criterion) can be modeled and solved.

Closely related to decision trees and often used in conjunction, influence diagrams are a summary of information contained in a decision tree. They involve 4 variable types for notation: a decision (a rectangle), chance (an oval), objective (a hexagon), and function (a rounded rectangle). Influence diagrams also use solid lines to denote influence. Their appearance is very similar to a flowchart.

Influence diagrams show the dependencies among variables. As illustrated below




Simple influence diagram for making decision about vacation activity

## Algebraic Models

An algebraic model takes a real-world situation described in words and describes that situation using algebra.

Some processes are so simple that they can be described in terms of algebraic equations, either explicitly, or implicitly as the solution to a differential equation. Algebraic equations are usually defined by applying some law of physics like conservation of mass or a time or space dependent equation describing the temporal movement of something. For example this is an explicit algebraic model: age = x – date of birth, where x is today's date.

## Spreadsheet Models

Spreadsheet formulae are used to relate various data values instead of algebraic equations or graphical representation. As spreadsheets are more widespread amongst business users, it is used for day to day decision making and modeling.

# 1.4. Problem Solving and Decision Making

Uncertainty and an overwhelming number of alternatives are two key factors that make decision making difficult. Business analytics approaches can assist by identifying and mitigating uncertainty and by prescribing the best course of action from a very large number of alternatives.

Business analytics involves tools as simple as reports and graphs, as well as some that are as sophisticated as optimization, data mining, and simulation.

## Problem Solving

It consists of using generic or ad hoc methods, in an orderly manner, for finding solutions to problems. Some of the problem-solving techniques developed and used in artificial intelligence, computer science, engineering or mathematics

Problem-solving is used in many disciplines, with different perspectives, and often with different terminologies. For instance, it is a mental process in psychology and a computerized process in computer science. Problems can also be classified into two different types (ill-defined and well-defined) from which appropriate solutions are to be made. Ill-defined problems are those that do not have clear goals, solution paths, or expected solution. Well-defined problems have specific goals, clearly defined solution paths, and clear expected solutions.

Being able to solve problems sometimes involves dealing with pragmatics (logic) and semantics (interpretation of the problem). The ability to understand what the goal of the problem is and what rules could be applied represent the key to solving the problem. Sometimes the problem requires some abstract thinking and coming up with a creative solution.

Problem-solving strategies are the steps that one would use to find the problem(s) that are in the way to getting to one's own goal. Some would refer to this as the 'problem-solving cycle'. In this cycle one will recognize the problem, define the problem, develop a strategy to fix the problem, organize the knowledge of the problem cycle, figure-out the resources at the user's disposal, monitor one's progress, and evaluate the solution for accuracy. The reason it is called a cycle is that once one is completed with a problem another usually will pop up.

The following techniques are usually called problem-solving strategies'

- ✓ Abstraction: solving the problem in a model of the system before applying it to the real system
- ✓ Analogy: using a solution that solves an analogous problem
- ✓ Brainstorming: (especially among groups of people) suggesting a large number of solutions or ideas and combining and developing them until an optimum solution is found
- ✓ Divide and conquer: breaking down a large, complex problem into smaller, solvable problems
- ✓ Hypothesis testing: assuming a possible explanation to the problem and trying to prove (or, in some contexts, disprove) the assumption
- ✓ Lateral thinking: approaching solutions indirectly and creatively
- ✓ Means-ends analysis: choosing an action at each step to move closer to the goal
- ✓ Method of focal objects: synthesizing seemingly non-matching characteristics of different objects into something new
- ✓ Morphological analysis: assessing the output and interactions of an entire system
- ✓ Proof: try to prove that the problem cannot be solved. The point where the proof fails will be the starting point for solving it
- ✓ Reduction: transforming the problem into another problem for which solutions exist
- ✓ Research: employing existing ideas or adapting existing solutions to similar problems
- ✓ Root cause analysis: identifying the cause of a problem
- ✓ Trial-and-error: testing possible solutions until the right one is found

## Decision Making

Decision-making is directly associated with selecting one course of action among two or more possible alternatives. Decision-making is driven by a desire to solve problems or exploit opportunities. A problem refers to some type of event that requires a response to avoid a negative consequence. Conversely an opportunity is an event or situation where a response is required to make something desirable happen.
It can be regarded as a problem-solving activity terminated by a solution deemed to be satisfactory. It is, therefore, a process which can be more or less rational or irrational and can be based on explicit knowledge or tacit knowledge.

Human performance with regard to decisions has been the subject of active research from several perspectives:

- ✓ Psychological: examining individual decisions in the context of a set of needs, preferences and values the individual has or seeks.
- ✓ Cognitive: the decision-making process regarded as a continuous process integrated in the interaction with the environment.
- ✓ Normative: the analysis of individual decisions concerned with the logic of decision-making and rationality and the invariant choice it leads to.

A major part of decision-making involves the analysis of a finite set of alternatives described in terms of evaluative criteria. Then the task might be to rank these alternatives in terms of how attractive they are to the decision-maker(s) when all the criteria are considered simultaneously. Another task might be to find the best alternative or to determine the relative total priority of each alternative

Decision making is the process of making choices by setting goals, gathering information, and assessing alternative occupations. There are seven steps in effective decision making, which are

- ✓ Step 1: Identify the decision to be made. You realize that a decision must be made. You then go through an internal process of trying to define clearly the nature of the decision you must make. This first step is a very important one.
- ✓ Step 2: Gather relevant information. Most decisions require collecting pertinent information. The real trick in this step is to know what information is needed, the best sources of this information, and how to go about getting it. Some information must be sought from within yourself through a process of self-assessment; other information must be sought from outside yourself-from books, people, and a variety of other sources. This step, therefore, involves both internal and external “work”.
- ✓ Step 3: Identify alternatives. Through the process of collecting information you will probably identify several possible paths of action, or alternatives. You may also use your imagination and information to construct new alternatives. In this step of the decision-making process, you will list all possible and desirable alternatives.
- ✓ Step 4: Weigh evidence. In this step, you draw on your information and emotions to imagine what it would be like if you carried out each of the alternatives to the end. You must evaluate whether the need identified in Step 1 would be helped or solved through the use of each alternative. In going through this difficult internal process, you begin to favor certain

alternatives which appear to have higher potential for reaching your goal. Eventually you are able to place the alternatives in priority order, based upon your own value system.

- ✓ Step 5: Choose among alternatives. Once you have weighed all the evidence, you are ready to select the alternative which seems to be best suited to you. You may even choose a combination of alternatives. Your choice in Step 5 may very likely be the same or similar to the alternative you placed at the top of your list at the end of Step 4.
- ✓ Step 6: Take action. You now take some positive action which begins to implement the alternative you chose in Step 5.
- ✓ Step 7: Review decision and consequences. In the last step you experience the results of your decision and evaluate whether or not it has "solved" the need you identified in Step 1. If it has, you may stay with this decision for some period of time. If the decision has not resolved the identified need, you may repeat certain steps of the process in order to make a new decision. You may, for example, gather more detailed or somewhat different information or discover additional alternatives on which to base your decision.

Biases usually creep into decision-making processes, like

- ✓ Selective search for evidence or confirmation bias: People tend to be willing to gather facts that support certain conclusions but disregard other facts that support different conclusions. Individuals who are highly defensive in this manner show significantly greater left prefrontal cortex activity as measured by EEG than do less defensive individuals.
- ✓ Premature termination of search for evidence: People tend to accept the first alternative that looks like it might work.
- ✓ Cognitive inertia is unwillingness to change existing thought patterns in the face of new circumstances.
- ✓ Selective perception: People actively screen out information that they do not think is important. In one demonstration of this effect, discounting of arguments with which one disagrees (by judging them as untrue or irrelevant) was decreased by selective activation of right prefrontal cortex.
- ✓ Wishful thinking is a tendency to want to see things in a certain – usually positive – light, which can distort perception and thinking.
- ✓ Choice-supportive bias occurs when people distort their memories of chosen and rejected options to make the chosen options seem more attractive.
- ✓ Recency: People tend to place more attention on more recent information and either ignore or forget more distant information. The opposite effect in the first set of data or other information is termed primacy effect.
- ✓ Repetition bias is a willingness to believe what one has been told most often and by the greatest number of different sources.
- ✓ Anchoring and adjustment: Decisions are unduly influenced by initial information that shapes our view of subsequent information.

# Certifications

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- Certified Business Accountant
- Certified Commercial Banker
- Certified Foreign Exchange Professional
- Certified GAAP Accounting Standards Professional
- Certified Financial Risk Management Professional
- Certified Merger and Acquisition Analyst
- Certified Tally 9.0 Professional
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**Big Data**
- Certified Hadoop and Mapreduce Professional

**Cloud Computing**
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- Certified Interior Designer

**Digital Media**
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- Certified Inbound Marketing Professional
- Certified Digital Marketing Master

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- Certified Human Resources Manager
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**Project Management**
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**Real Estate**
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**Marketing**
- Certified Marketing Manager

**Quality**
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- Certified Six Sigma Black Belt Professional
- Certified TQM Professional

**Logistics & Supply Chain Management**
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- Certified Logistics & SCM Professional
- Certified Purchase Manager
- Certified Supply Chain Management Professional

**Legal**
- Certified IPR & Legal Manager
- Certified Labour Law Analyst
- Certified Business Law Analyst
- Certified Corporate Law Analyst

**Information Technology**
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- Certified Basic Network Support Professional
- Certified Business Intelligence Professional
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- Certified E-commerce Professional
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**Mobile Application Development**
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- Certified Corporate Social Responsibility Professional

**Life Skills**
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- Certified Advertising Sales Professional

**Sales, BPO**
- Certified Sales Manager
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