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Review Article

Decision Support Systems: A Lifeblood to Organizational Data-based Decision-making

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Abstract

Data has become an essential business commodity, from the historical data challenge of an organization and its storage solutions, data management solutions, to algorithms and data solvency considerations. One of the most critical steps in building a competitive organization is finding a functional, data-based, and competent decision-making platform. A good decision support system, therefore, combines historical data with current data, and computational data to empower organizational management to make the most appropriate, and current decisions based on the best possible data for the organization. A decision support system is a systematic tool engineering management may use to make difficult decisions for an enterprise. In this paper, we diagram and outline three possible working decision support systems useful for empowering management with the best tools possible to make key decisions. Firstly, we outline three diagrams of decision support systems and discuss the usefulness, challenges and weaknesses, and strengths. Next, in this review paper, we apply current business situations and look at the usefulness of the models.

Keywords: Decision Support System; Data Warehouse; Big Data; Computational Decision Making; Data Lakes

Introduction

The role of management in any organization is to make decisions, support creativity, engineer ingenuity, motivate employees, etc. In any organization, managers can use Decision Support Systems (DSSs) to make important decisions, calculate difficult equations, assist and support decision-making by subordinates, and assist in making medically difficult diagnoses in the practice of precision medicine [1]. Managers must also use decision-making skills to motivate their employees to make appropriate decisions and encourage subordinates to work independently, be effective and efficient in their work roles, and establish a good partnership between subordinates and supervisors. A symbiotic relationship between subordinate employees and employers can develop when there is mutual respect and a symbiotic mutualism for improving performance and achieving company goals as the leadership style motivates subordinates to the point where there is an impact on company goals. Therefore, the use of various DSSs can influence any number of leadership factors. For example, by using artificial intelligence, management can influence subordinates and even influence management style [1].

Financial institutions rely on management to make decisions on how to implement automatic fraud detection systems to detect and block fraudulent transactions in a data-driven society. Using a DSS, managers can analyze factors including social media profiles and posts, tweets, and other postings that may be suspicious or lead to an investigation into banking transactions. A data-driven DSS can be valuable in the automatic detection and blocking of fraudulent transactions by using a machine learning algorithm [2]. The task of detecting fraudulent transactions is a binary classification problem that can attract many techniques. However, for management to have interpretability, or confidence in the model, which is highly important when searching out fraud by allowing experts to search for fraudulent activities and flag them for later exploration. The use of artificial intelligence, is again, of the utmost importance in a sustainable model [2].

Wuryani., *et al*. [3] present a DSS that evaluates each employee's performance using a situational leadership framework that defines the variable work motivation via a survey. This quantitative method uses a saturated sample and multiple respondents that will increase the research and retain a more pertinent sample and make the results more objective. Using PLS 3.0 data analysis, researchers were able to demonstrate how the role of technology in any semi-structured decision-making process must provide sufficient data to improve the motivation and performance of any employee. Moreover, leadership is still used to make unstructured decisions without paying much attention to the unstructured data stored in the performance system [3].

Managers must become experts at making decisions and using DSSs is one method that managers can use. Mapping out decisions, using graphs and data, using decision trees, etc. are excellent methods for making decisions. However, decision-intensive business processes that gather multiple pieces of information and collaborate to decide based on all the information is fairly more complicated than a basic decision tree, therefore use of a DSS can be both objective and result in fewer errors and gathering of high-quality data in a complex yet readily available format to have available for contemplation when making the decision. A well-defined process for decision-intensive decision-making can be cost-effective and linked to a standard optimization format of Markov Decision Processing, which is also an optimal standardized information gathering process [4].

A good decision should be made with access to good information and high quality, efficient decision-making should be based on a link to variable sources of high-quality data. Such business decisions make high-quality data and require incredible flexibility. A DSS is used by decision-makers to make effective decisions or decisions that weigh all the alternatives and make the optimal decision regarding the "correct" decision. Hence, an engineer needs to gather the information regarding any decision and weigh the correct pathway through whatever means, and derive the costs and gains of the decision, making the least costly and the decision with the most gains [4].

Graphic representation of three decision support systems

A thorough understanding of the DSS enhances the use of the decision support mechanism. Decision-makers may be reticent to use statistical or machine learning models if is not clear how they achieve their decisions. Therefore, a graphical model that clearly outlines how the decision-maker reaches their decision is quite appropriate for use. Companies are collecting a wide variety of high-dimensional data for use in a DSS [5,6]. By definition, a DSS is a computer-based system combining data and decision logic which is used as a tool to assist a human decision-maker. Although the DSS assists the decision-maker, it does not make the decision. Instead, the DSS facilitates the human decision-maker by analyzing the inputted data and processed information and presenting it in a format friendly to the decision-maker [6]. The following figure 1 depicts the proposed contents of any successful DSS [5].

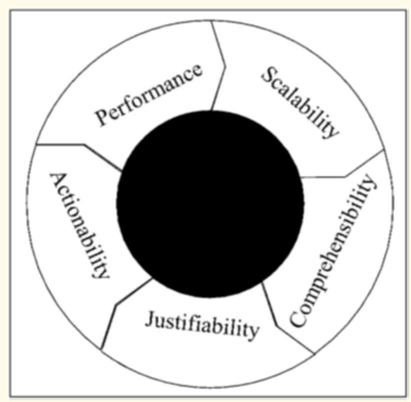

Figure 1: The Proposed Contents of a Successful DSS.

Collaborative decision support system for automatic clustering

Figure 2 outlines the pathways that an engineering manager must decide on when making the most efficient and cost-effective decision for the company. Many times, there is not an abundance of data for human decision-making however, with the DSS, decision-making plays a prominent role and considers all the vital steps. Thus, the engineer is well prepared to make a more educated and thorough decision. Figure 2 is a graphic representation of the Jabbari., *et al*. [7]. Collaborative Decision Support System for automatic clustering, which is useful when the management has little or no information about a complicated problem. A lack of generalizability in the current automatic clustering indices fosters a challenging framework for decision-making for the manager. A select number of evolutionary algorithms are chosen among the clustering indices and given the decision-maker's knowledge on the subject, a mixed-integer, non-linear programming model can be developed and given the decision-makers confidence in their knowledge on the subject, the best Vis, and the worst are selected for the outcomes so that the decision-maker may use them for final decision-making. Notice the emphasis given to the qualitative indices [7].

The most important factor in cluster analysis is determining the number of clusters because this will have a dramatic effect on the clustering analysis. Clustering analysis has been applied in numerous applications from banking and finance to retail communications and vaccine distribution networks such as those seen in the 2020 COVID-19 Pandemic. There are two types of clustering: automatic, where the number of clusters is fixed; and variable, where the best number must be determined by an efficient and knowledgeable decision-maker. Determining the number of clusters becomes even more complicated as several situations develop into situations where the dataset has many dimensions and choosing the right parameter must be done by a knowledgeable decision-maker. Validity indices (VIs) measure the fit based on the index's predetermined criteria. Some datasets, however, can have various geometric structures, and the decision-maker must decide which parameter best fits the cluster [7].

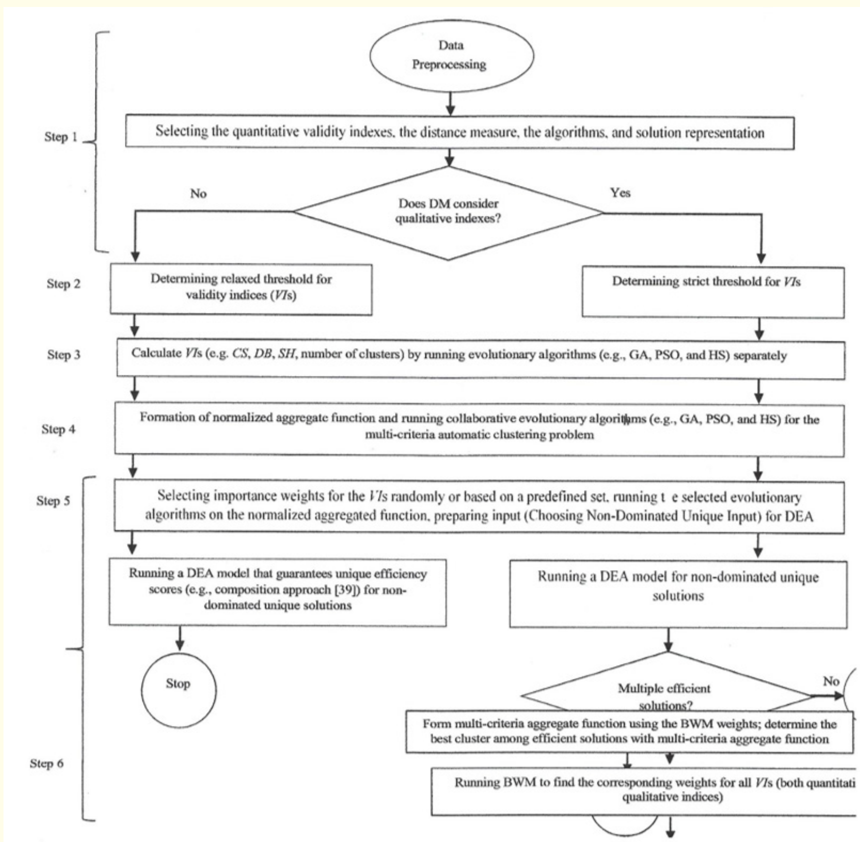

Figure 2: Graphic representation of the decision tree of the Collaborative Decision Support System for automatic clustering.

Multi-criterion intelligent decision support system for COVID-19

The question that decision-makers want to ask is if "information can travel faster than the virus which started in Wuhan, China and has now spread worldwide, how much faster must decision-making be" [5]. The entire idea behind this decision-making tool is accountability and support. It is necessary to transition far beyond recognition apps and tools such as Aarogya (India) and (Germany), proximity tracing to machine learning algorithms and deep learning techniques with AI that deliver an associated accurate model of prediction, vaccination, etc. [5].

An additive Utility Assumption Approach for the Criterion Comparison in the Multi-criterion Intelligent Decision Support System (MCIDSS) for COVID-19. This dataset and decision support tool for managers, stakeholders and other decision-makers has been gathered from a variety of sources such as the government link for validating the results. This DSS model, with an accurate prediction of identified risk factors based on specific well-defined input parameters, has been proposed and validated empirically using the standard SEIR model approach (i.e., Susceptible, Exposed, Infected, and Recovered). This machine learning technique results in a tabular analysis of risk factors that include well-known criteria and a comparative analysis of proposed approaches.

In today's pandemic, there are massive amounts of data being collected about the coronavirus, making it critical to sort and assimilate information into pertinent and useful information for making ubiquitous decisions for humankind globally [5]. So, to reduce human interaction and chances for human mistakes, the MCIDSS was developed so that the multiple factors associated with COVID-19 infection could be assessed at once and evaluated for specific parameters without human intervention. The MCIDSS can take multiple, usually conflicting data and formally incorporate them into a management plan. The prediction of some COVID-19 models has become nationalized, and authenticity is not guaranteed from place to place. Therefore, information from point-of-care models such as MCIDSS can reform the inaccuracy of previous COVID-19 models. Various data, such as demographic, GPS, vaccination status, vital signs, etc., as well as other data such as diabetes or other comorbidities, nutritional level, etc. can make the current DSS much more effective than previous models [5]. Figure 3 and Figure 4 [5] demonstrate the process of the MCIDSS and the decision-making process.

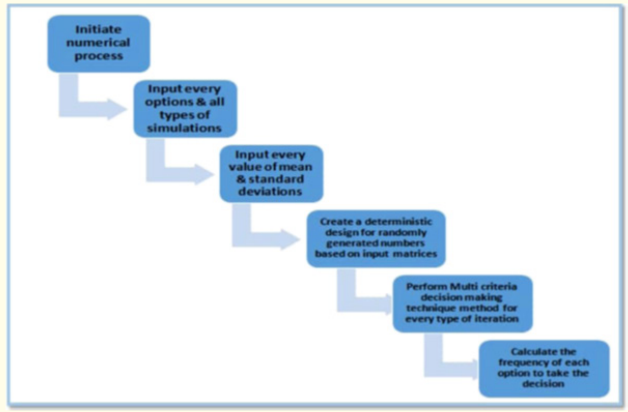

Figure 3: Illustration of the block diagram of the MCIDSS.

Figure 4: Flowchart demonstrates MCDSS decision-making process.

A probabilistic bayesian inference model

Big Data analytics is used to examine huge amounts of data; records and pieces of information to determine patterns, actionable insights, and interpretable results to mine hidden patterns, variable domains, and commonalities, just to name a few. Many valuable areas of data have been examined for their potential to leverage the value of big data. Healthcare, finance, business, etc. have been able to use big data in making decisions and determining worthy data for analysis. However, no area has more importance than auto accidents and reconstruction of accident sites to make accurate decisions regarding an in-depth analysis and an understanding of the traffic accident. Although probabilistic modeling makes good sense for traffic scenarios, the use of big data models can also provide an understanding of the risks and provide measures for preventing the same accidents from occurring again [8].

The main objective of a data science model is to identify high-risk factors with apparent significant influence on the probability of injury severity in automobile crashes while using a GPS car crash dataset. For accurate, reliable, and intuitive results, a multi-step probabilistic inference model based on Bayesian Belief Network which is a highly acclaimed machine learning methodology is proposed to make better decisions. An underlying inference model will provide scientists with a critically accurate method to explore the domain while disengaging issues related to statistical correlation and causal effects. In this model, creators made a publicly available tool to assist decision-makers with conducting what-if analyses on variable interdependence [8]. Innovative and creative safety measures are continually being upgraded into vehicles. It is necessary to have a method to interface with these measures and consider them when making decisions. And defects are unavoidable in the manufacturing process, making it a priority for the decision-maker to consider these variables when making the decision [9]. The amount of manufacturing data has multiplied greatly over the last few years and now requires intelligent systems to extract the data and pull together a workable decision [8,9].

The Probabilistic Bayesian Inference model provides the decision-maker access to information and tools that the mind alone cannot pull out from the massive amounts of data [8]. But because the decision-maker needs to consider multiple datasets such as manufacturing defects, raw material defects, production defects, etc.; making these data-driven decision-making support systems great tools for management to utilize so that not only quality but also quantity is maintained [8,9].

In figure 5 [8], a Probabilistic Bayesian Inference model is demonstrated. Using raw data and big data technology such as deep learning and artificial neural networks, data is organized for the decision-making process into rational, logical, and organized sections that consider patterns and probable outcomes [8].

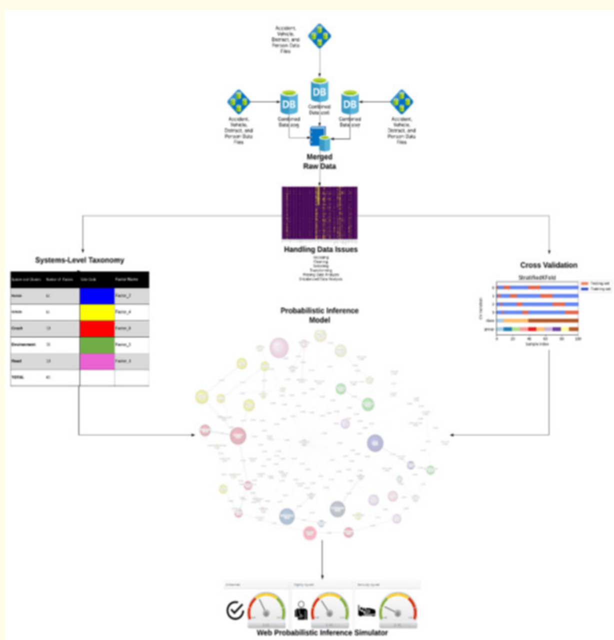

Figure 5: A Probabilistic Bayesian Inference model is demonstrated.

Conclusion

As demonstrated by the previous models and diagrams, decision-making can be assisted in various ways using a variety of methods from big data to artificial intelligence. The computer can assist the decision-maker in considering many more variables than humanly possible otherwise. For example, when considering COVID-19 cases, numerous parameters of data must be considered by the decision-maker. However, with the assistance of either of these DSSs, raw data, production data, human data, and other data can all be combined into the logical form of a DSS, and a logical output is received.

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