TOWARDS A SYNTHESISED DECISION SUPPORT METHODOLOGY THAT INTEGRATES HUMAN COGNITION AND DATA MINING

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Abstract

Developments in information and computing technologies have given rise to Intelligent Decision Support Systems (IDSS). The design of IDSS is largely based on data mining techniques and fuzzy logic. While decision-making is an advanced cognitive process, very little has been done in developing decision support methodologies that help integrate high level cognitive human reasoning and thinking elements within IDSS. This paper proposes a new IDSS methodology that incorporates both data mining techniques and human cognition in the process of decision-making. This proposed methodology involves a phased decision-support process. The initial phase focuses on phrasing a decision based on important criteria or conditions. The second phase involves the machine to analyse the required information from one or more large datasets. The third phase involves human cognition in making intelligent decisions based on key cognitive elements. Furthermore, the proposed methodology is tested on a large data set in the context of elderly care units in Melbourne.

Keywords: Intelligent Decision Support Systems (IDSS), data mining, human cognition, decision making, clustering

1 INTRODUCTION

A key role of decision makers in organizations concerns the evaluating and ranking of possible decision criteria that may lead to appropriate action (Malakooti 2012). According to Franklin (2013), a decision maker: (1) looks into the pros and cons of each action, (2) considers all the alternatives for a successful outcome, (3) is expected to predict outcomes of each option for any given situation, and (4) based on all these criteria, determines the best option suitable. Nowadays, technology plays a vital role in helping humans take decisions in an effective way by processing the data, analysing the data and providing alternatives to choose from. There are several information systems that have emerged in the past few years, referred to as Decision Support Systems (DSS), which help decision makers to identify and solve problems by making the right decisions utilizing large datasets and different models available (Polič 2009). The advent of emerging technologies such as Artificial Intelligence (AI) in the Information and Computing industry, has given rise to a new form of DSS called Intelligent Decision Support Systems (IDSS). An IDSS is a decision support system that acts like a human consultant supporting decision makers in acquiring and evaluating data and making final decisions (Jantan et al. 2010; Phillips-Wren 2012).

Most of the new generation IDSS use a combination of Online Analytical Processing (OLAP), data mining techniques and fuzzy logic to process large volumes of data to come to one or more conclusions. By making use of these state-of-the-art computing technologies, IDSSs are able to perform some selected cognitive decision-making functions. However, perfect design of IDSS is still largely based on human decision-making mechanisms including human cognition and experiences of specific contexts, and behaviour. Top-level management in an organization who generally participates in decision-making processes might not have high-level knowledge in mathematics and/or computer science to use IDSS. Considering this scenario, very little has been done in developing DSS's that help harness high level human cognitive reasoning and thinking elements (Franklin 2013). There is a need for a methodology that explores the complementary nature of emerging IDSS technologies and human cognitive abilities as antecedents for effective, intelligent decision-making. This study therefore aims to address this limitation by answering the following research question:

How can organizational decision-making be improved using human cognition and machine intelligence?

In addressing this research question, this research in progress proposes a new IDSS methodology that incorporates human cognitive elements with a data mining technique called 'clustering' to help managers both IT and non-IT environments, sift through and reason out relevant information from large data sets in an easy, effective and timely fashion. The next section reviews key literature on traditional decision support systems, new trends in decision-making tools and then reviews how human cognition is used in decision-making. Section 3 illustrates the research approach, followed by Section 4 that proposes a new IDSS methodology. The proposed methodology is then tested in a practical scenario (Section 5). Finally, the paper concludes with some future scope of the research.

2 BACKGROUND

Existing literature indicates that from late 1960s to 1990s, researchers mainly focused on developing model-driven DSS (Power 2007), financial planning systems, spreadsheet-based DSS and group DSS (Chai et al. 2011). Data-driven DSS such as data warehouses, executive information systems, Online Analytical Processing (OLAP) and business intelligence systems emerged during the same period (Power 2007). The advent of the World Wide Web and other computing technologies in the mid 1990's led to a rise of knowledge driven DSS and web-based DSS (Bhargava et al. 2001).

In recent years, several decision support systems have facilitated the use of deductive and inductive approaches to decision-making. Advanced data analysis systems such as Online Analytical Processing (OLAP) systems follow a deductive or analytical approach in their modelling. While using these approaches and with the increase in data volume, even the best analysts find it difficult to drill down and consider several alternatives for recognising patterns, trends and valuable information (Rok et al. 2007).

Data mining is defined as the process of discovering patterns in data from large databases to support the analysis of the data (Witten et al. 2005). Data mining helps to: understand information present in the data sets, carry out predictions and trend analysis, and perform clustering based on certain specific criteria or queries selected. The use of data mining techniques has helped resolve some of the difficulties associated with sifting through large data sets. These techniques are easier to analyse and also visually more interesting to suffice non-technical decision makers (Rok et al. 2007). Data mining models can be grouped into two main classes according to their goals: supervised or predictive models (classification and regression) and unsupervised or descriptive models (summarization, clustering and methods for association rule mining). Important techniques that are part of the supervised and unsupervised models, and widely used algorithms for each of these techniques are described in the Table 1.

Data mining techniques	Description	Algorithms used
Classification	A function that maps each data item to one of the several available classes, which are predefined. *Ex: Classifying financial market trends*	Decision trees, rule-based induction, neural networks, memory (case) based reasoning, genetic algorithms, bayesian networks
Regression	Predicts the value of a data item based on other real value variables. *Ex: Predicting the demand of a newly launched product based on expenditure for the ads*	Linear regression, nonlinear regression
Clustering	Identifies similar data sets and forms them into groups. *Ex: Clustering data sets based on the population density of a suburb*	K-means, DBSCAN, Cobweb, EM, Farthest First
Association	Uses if/then statements that uncover relationships between apparent unrelated data in a large data set *Ex: A customer buying products x1 and x2 will also buy product y with a certain probability*	Apriori (using Breadth first search), Eclat (using Depth First search), FP-Growth (frequent pattern)
Summarization	Finds a compact description for a subset of data. *Ex: Tabulating the mean and standard deviation for all the fields.*	Keyword summaries, sentence extraction, natural language understanding/generation

Table 1: Data mining techniques and algorithms used for each technique

Furthermore, as the decision-making process have encountered more fuzzier situations and unstructured managerial problems, newer intelligent techniques that can handle human reasoning and learning have come into existence, which are again embedded in DSS. In this case, the DSS application’s name is given based on the intelligent techniques that they use, such as expert systems, rule-based systems, Knowledge Based Systems (KBS), fuzzy sets, and Neural Networks (Jantan et al. 2010). However, these intelligent techniques are more specific to chosen fields such as usage of fuzzy DSS in e-commerce and tactical decision-aid systems to support military planning operations (Grasso et al. 2006; Mittal et al. 2013; Ngai et al. 2005). According to Shim et al. (2002), the future of DSS is web-based, where a typical browser serves as the user interface for the decision makers. DSS to date have supported deductive and inductive styles in various ways but having only a technical perspective presented by these systems is not enough for decision-making. Personal perspectives, organizational views, ethical and aesthetic issues need to be considered for effective decision-making (Courtney 2001).

According to Liu et al. (2012), "decision-making is an advanced cognitive process". People would not only want to choose the best alternative but also focus on selecting the most effective and best fit for their goals, desires, lifestyle and values. Li et al. (2010) highlight that an entrepreneur's mental model while making strategic decisions, may be influenced by cognitive factors such as *beliefs, values, schemas, emotions and feelings*. A study by Pohl (2008) suggests six functional elements that form the nature of decision-making: *information* (factual data and details of the problem or situation), *representation* (the way objects are presented and described), *visualization* (mechanisms to visually communicate and present information), *communication* (channels for social interaction), *reasoning* (drawing deductions and inferences from information), and *intuitio*n (spontaneous knowledge transfer to a new domain). Another study suggests that crucial human factors such as personality, culture, values, intuition, and emotions are important internal factors inherent to decision-makers (Barsnick 2002). According to Barsnick (2002), expertise, stress and risk form external factors that are determined at the time of making the decision. With the help of technology used in DSS discussed earlier, though people can improve their working efficiency, in most fuzzy situations the final judgment of decision makers is dependent on their inherent gut feeling (Liu et al. 2012). In addition, apart from having practical knowledge of the decision task, other important aspects that affect decision makers are the "personality type, cognition, decision style, company position, and objectives of each decision maker" (Karacapilidis 2006). Thus, to overcome the gap between human and machine interaction especially while modelling DSS, a methodology is required that emulates decision makers' cognitive abilities, in addition to data mining concepts for timely and effective decision-making.

Based on the existing literature it is observed that either data mining techniques or fuzzy logic using human cognition have been used in different fields of study to make decisions. In this paper we argue that a DSS that combines *both* aspects: (1) data mining techniques/tools to help handle large datasets and (2) use of human cognitive elements, is necessary to help managers in organizations make effective, accurate and timely decisions. This study therefore proposes a design methodology that incorporates both machine and human cognitive abilities into a DSS in a simpler and easily implementable manner.

3 RESEARCH APPROACH

The aim of this study was to address the research question: *How can organizational decision-making be improved using human cognition and machine intelligence*? To answer this question, the research approach undertaken in this study consisted of: (1) a literature review, (2) designing a new methodology to develop an IDSS using relevant literature that can be used by managers, (3) identification of large datasets in the health care sector, (4) interviews with some decision makers from different organizations, and (5) finally testing the proposed methodology.

This research started by reviewing current literature on various DSSs developed and used in the IT field. Keywords that were used to search for relevant research papers included DSS, IDSS, human cognition, human cognition and data mining. Most of the DSS research was based on analysing trends using historical data and predicting results needed to support decisions. There were some DSS called intelligent decision support systems that focus on introducing data mining, fuzzy logic and fuzzy cognitive mapping (Witten et al. 2005; Grasso et al. 2006; Mittal et al. 2013). About fifty papers were reviewed that discuss IDSS and how human cognition is embedded into DSS. Most articles focused on developing decision support systems for specific contexts. It was also observed that only a few studies focussed on using *both* machine intelligence using data mining and human cognition for DSS, to sift through large datasets and aid managers to make decisions in a simple, efficient and meaningful way. Also, few of the studies that developed IDSS using data mining techniques and human cognition, were context specific. This lack of a combined approach to decision making prompted a need for a different methodology that involves *both* machine intelligence and human cognition a single DSS that would be easy to implement, understand and use by organizational decision makers.

In this paper, we propose a methodology that uses both data mining techniques and human cognition. The proposed methodology consists of three phases – Phase 1: decision criterion; Phase 2: usage of machine and data mining techniques and; Phase 3: application of human cognitive elements. From exiting literature, we collated important human cognitive elements for effective decision-making and used an intelligent data mining technique called clustering. The methodology therefore uses the machine, a data mining technique and also encapsulates human cognition elements for decision-making. To validate these human cognitive elements, we conducted informal interviews with seven managers from IT and non-IT firms to capture their views about the important cognitive elements they use while decision-making. It is important to note that the informal interviews were treated only as a pilot to confirm common human cognitive elements used by decision makers.

The proposed methodology was then tested on a large dataset synthesized from Victorian government websites in the aged-care context, with a real-world decision scenario of whether or not it is profitable for a decision maker to establish an elderly care unit in one of the Melbourne suburbs. To start the testing process, a senior decision maker from an aged care sector was interviewed to gather some information about important criteria required to start an elderly care unit. Further, based on the inputs and data availability, the datasets were pre-processed to make it suitable for the data-mining tool called WEKA (Hall et al., 2009). Waikato Environment for Knowledge Analysis (WEKA) is recognized as a comprehensive system in data mining and machine learning. It provides a wide-ranging collection of machine learning algorithms and data pre-processing tools for users to easily compare different machine learning methods on new data sets. The proposed framework was then tested and validated against a large dataset and this methodology provided results that help a manager decide where he would be able to start an aged care unit based on profitability.

4 NEW METHODOLOGY FOR IDSS DEVELOPMENT

In this section, we introduce a new methodology for development of an IDSS that incorporates both machine intelligence and human cognition. The proposed methodology involves three phases:

1) Phase 1 is the initial phase that involves the role of a decision maker - to reflect, reason and decide on important decision criteria/queries that he/she has to consider for a decision to be made, based on his/her existing knowledge expertise;

2) Phase 2 involves using the *machine* to help decision makers with the analysis of required information gathered from huge datasets, using decision criterion in Phase 1. Phase 2 involves the processing of large volumes of data that cannot be handled by humans using data mining techniques such as clustering. At the end of Phase 2 a decision maker would have some alternatives at hand and;

3) Phase 3 involves a *human* to make the right decision(s) based on the most important cognitive elements that influence human decision-making abilities. These cognitive elements are applied to the alternatives in Phase 2 and the most effective alternative is chosen for decision making.

Figure 1 represents the proposed IDSS methodology showing the three phases and the important steps in each phase of the methodology. The following sub sections describe each of the phases.

When a decision is to be made, phrasing it according to the criteria is a primary task. For example, a criterion could be a request from an external organisation that considers to: “*Start an elderly care unit in a suburb in Melbourne”*. But it would be useful if the decision phrase had more descriptive and/or qualifying information that aids decision-making, according to the actual flow of thought.

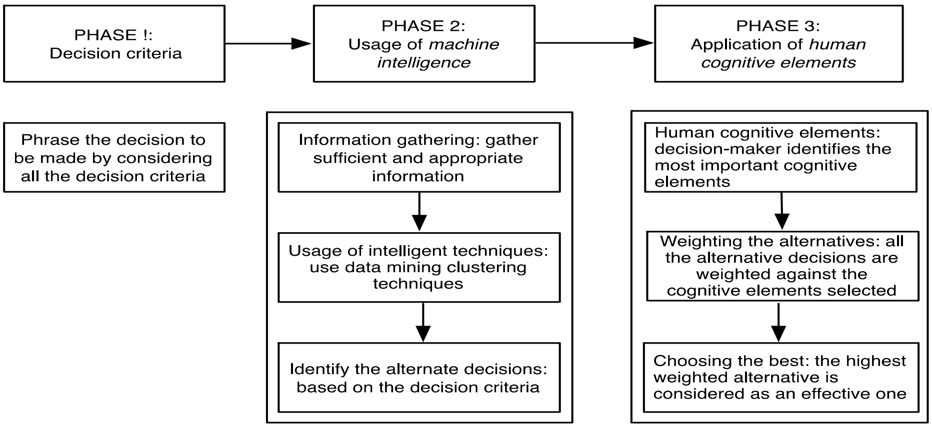

Figure 1: The proposed IDSS methodology

4.1 Phase 1: Decision criteria

That is, we could have a criterion that states *starting a commercial elderly care unit in Melbourne in a suburb, which is economical and convenient*. This phrase gives a richer view on the actual decision that has to be made. The outcome of the decision should satisfy important factors in the phrase, such as, the elderly care unit should provide *commercial success* to the organization; it should be *economical* for the organization in terms of expenditure and must have *convenient access* to transport and other facilities for the elderly that stay in these care units. Knowing what we actually need would help in choosing the best alternatives. In order to phrase the decision and look for information/inputs that is important that decision makers experience and knowledge in the specific area is crucial. It is therefore necessary for a decision maker to consider all the factors such as budget, expenditure, convenience, resources, clients and other requirements, and then phrase a decision criterion.

4.2 Phase 2: Usage of machine

Once the decision is phrased, the important steps in Phase 2 are: (1) gathering relevant information, (2) usage of intelligent techniques and tools, and (3) identifying the best decision alternatives.

Information gathering: Information relevant to the specific context is gathered from various data sources. This information should be accurate and provide enough details for the decision to be made. Aiming to include all the data available may delay the decision-making process. In order to suffice the format that is accepted by data mining techniques, the data gathered should be pre-processed. Pre-processing of the data includes preparing and formatting the data through scrubbing e.g. removing duplicates and correcting capitalizations.

Usage of intelligent techniques: The large data sets that available at this stage, makes it impossible for decision-makers to analyse and choose the best alternatives, identify patterns, trends and make sense of the available data. This is where the power of the *machine* using data mining plays an important role. The results obtained by using one or more data mining techniques can be presented in a visually interesting way that makes it easier to understand the result of data-mining for non-technical users (Fayyad et al. 1996; Tsiptsis et al. 2011). In this study, we used ‘clustering’ as the data mining technique to analyse the data. The advantage of clustering is that it can be performed on both heterogeneous attributes and large datasets (Berkhin 2006). This makes it easier for a decision maker to eliminate one or more clusters from the larger dataset in the event that these do not fit the decision maker’s decision criteria.

Identifying the decision alternatives: Based on results obtained from clustering as performed by the machine, the best suitable alternatives can be identified. Choosing the best alternatives is related to the decision criteria chosen in Phase 1 and the information gathered. The steps in identifying the decision alternatives include: Step 1: Identify the clusters and in particular, the data sets in those clusters that are most suitable to the criteria determined in Phase 1, Step 2: Eliminate the remaining clusters that do not match the decision criteria, and Step 3: The data sets are further analysed to match the decision criteria. This is an iterative process that will narrow down the data sets, and Step 4: a set of best-suited alternatives is selected.

4.3 Phase 3: Application of human cognitive elements

After identifying the decision alternatives in Phase 2, a decision-maker has to work on essential cognitive elements in Phase 3 to make decision choices. The new IDSS at hand presents the most essential human cognitive elements to be considered while making any decisions. In Phase 3, the decision maker is taken through a series of steps such as identifying the human cognitive elements, weighting the alternatives chosen via a decision table and finally choosing the best one from those alternatives.

Human cognitive elements: Human cognitive ability plays an important role while making any final decisions. It enables decision-makers make most effective decisions and chooses the best alternative. Based on the existing literature discussed in Section 2, a number of cognitive elements that affect humans in their decision-making were identified: belief, value, intuition, emotion, schema, personality type, stress etc. To enhance understanding and strengthen the capturing of cognitive elements for effective decision-making, we conducted a pilot study and interviewed seven managers/technical leads generally involved in decision-making, to understand how decisions are taken in organizations. Some of their comments are summarized below:

A service delivery manager from a multinational corporation said "*The critical elements that drive towards effective decision-making are: problem identification, past experience, data analytics, 'thinking beyond' and SWOT analysis".* He also said: "*While making decisions our mind plays a vital role in utilizing logic and intuition. Logic mainly focuses on the facts and analytics whereas intuition resides in a subconscious mind that is mainly [geared] towards opinion, belief and arriving at a decision."*

A technical lead said: *"The important cognitive elements for decision-making are vision, intuition, cognitive inertia, group thinking and emotions".* Another manager commented that: "*Vision, emotional status of the team, expertise, and intuition were the essential cognitive elements that had to be considered while making a decision".*

Based on the cognitive elements identified in the existing literature and the information collected from different managers for this study, four important cognitive elements *vision, intuition, expertise* and *emotion* were considered and embedded into the methodology as shown in Table 2.

Vision: Vision plays a vital role in human cognition of decision-making. For effective decision-making the decision-maker should be well acquainted with answers to questions such as: what does the company aim to achieve as a primary objective in the future? Will the decision that is made, satisfy the future goals and aspirations of the organization? (Pohl 2008).

Intuition: A formal definition of intuition according to (Li et al. 2010) is: "A capacity for attaining direct knowledge or understanding without the apparent intrusion of logical inference". According to this definition, logical reasoning and the weightage of strengths and weaknesses of particular situations are not considered, but just the *gut feeling* of a person with little information or prior experiences.

Expertise: The more knowledgeable and experienced a decision maker is about a situation; the better s/he is in deciding the best alternative (Pohl 2008).

Emotion: Research has revealed the importance of examining emotions like anger and fear impact judgments and decision-making. Being positive while making a decision, will influence the mind in a positive way, allowing an effective decision, to be made (Pohl 2008).

A decision maker works on these elements for effective decision-making, depending on their state of mind and experience at the time.

Weighting the alternatives: The alternatives selected in Phase 2, are weighted against human cognitive elements. Table 2 describes the decision table, which can accommodate human cognitive elements, the priority of each and alternatives (choices). The decision-maker has to prioritize the cognitive elements and then s/he has to mark the highest priority element with the highest score, and lowest priority element with the lowest number. For example: How much does choice 1 satisfy the human cognitive element *vision*? A score on a scale of 1 -10 describes the weightage.

Choosing from the alternatives: Once priorities and choices are weighted against each human cognitive element, each priority number is multiplied with the corresponding choice. A decision-maker has to weight the choices with a number from 1 to 10 according to their preference. Thus all the choices are scored against the elements according to the priority and then summed up to form the final score. The choice with the highest score would be considered as the most effective decision. That is, this choice has navigated through all the important steps right from data mining to the most important elements that effect human cognition. The choice supports all the business analytics and human factors and is considered to be the best decision based on all the criteria at hand.

COGNITIVE ELEMENTS --->		Vision		Intuition		Expertise		Emotion	
	Priority								
ALTERNATIVES									**SCORE**
Choice 1:									
Choice 2:									
Choice 3:									
Choice 4:									

Table 2: Decision table with human cognitive elements and priority

5 TESTING THE PROPOSED IDSS METHODOLOGY

Part of the pilot study involved the testing of the proposed IDSS methodology in a real-life situation, i.e in an aged-care context using the Victorian government website that provides large datasets of information about suburbs, age profile of people residing in those suburbs, transport facilities, availability of shopping centres, hospitals and so on. For example, an organization might have the intention of starting an aged care unit in a suburb in Melbourne. A suburb to start an elderly care unit is chosen based on the decisions provided by our new proposed IDSS methodology using the following three phases, as well as datasets from the Victorian websites and inputs from managers in organizations.

5.1 Phase 1

In Phase 1, a decision-maker decides on the decision criteria. In this study, to understand the important criteria for starting an elderly care unit in Melbourne, a decision-maker who works as a data analyst with one of the nursing services in Melbourne was contacted to garner her initial thoughts in the form of decision-criteria on this issue. Based on her experience, an elderly care unit should be started in a suburb where the income, age, and health of the elderly individuals are all ‘good’. The suburb shouldn’t have any other aged care unit with a similar cultural background. Other resources like: land availability or properties, government rules and regulations should also be considered. Decisions on whether it should consider opening a private or funding-based care unit; its size; how many beds it can accommodate; delivering aged-care with the most economical human resources, balance with quality care, are important aspects for consideration. Population might not be a concern, but the environment is important. Good knowledge on the suburbs is also required. Based on inputs from the analyst and data availability, the following criteria were taken into consideration:

- Cost /budget, i.e. the suburb shouldn't be too costly to start an elderly care unit.
- Suburb with a high population of the elderly.
- A suburb that has most of the amenities e.g. fresh markets, police stations, parks, libraries, recreational centers, hospitals, shopping malls and transportation were considered.
- Most primarily a suburb with less or no competition (i.e. no existing elderly care units) was also considered.

Thus, starting an elderly care unit in Melbourne can be re-phrased as: *Starting up a commercial elderly care unit in Melbourne in a suburb that is both economical and convenient*.

5.2 Phase 2

Information about the list of suburbs and appropriate information needed to meet the criteria were taken from the statistics present in the Victorian websites (State Library of Victoria. 2013; Department of Planning and Community Development. 2013; Victoria Police. 2013; Department of Health, 2013; Commonwealth of Australia, 2014; Ripefruit Media Co.; Wikipedia. 2014a,b; Fairfax Media. 2011). Once the data was gathered and collated into a single data set, the data was pre-processed[1] to remove duplicates, unwanted symbols, capitalization in between the lines, etc. to fit the **WEKA** data mining tool (Hall et al., 2009). Table 3 shows the sample dataset after pre-processing the collected data.

In this study, for the purpose of testing, the c*lustering* data mining technique was selected from WEKA. Specially, we used a clustering algorithm called *K-means* because the dataset collected was unsupervised and sum of the squared errors was less when compared to the other algorithms in clustering. In *K-means* algorithm, K-clusters are formed, and the average of each cluster's content determines its centroid. The centroids in this algorithm are recalculated as and when data is added until the point where the centroid doesn't change. Thus, a dataset of 411 rows and 19 columns of the suburb information collected were divided into 4 different clusters. These clusters that were formed have their own centroids and attributes corresponding to each centroid. Each instance in the dataset would be nearer to one of these centroids. Table 4 depicts the centroids and attributes of the 4 clusters formed. As shown in Table 4, for cluster 0 and 1 the suburb Abbotsford is its centroid, for cluster 2 the suburb Kalorama is its centroid and Alphington is the centroid for cluster 3. The attributes were: Melbourne suburbs, elderly care unit and public libraries.

According to the criteria considered in Phase 1, there should be *no* existing elderly care units and the suburb should be convenient and economical. In the graph shown in Figure 2, (X-axis Elderly care units, Y-axis Melbourne Suburbs), the '*no'*- right-hand side of the elderly care unit gives us all the suburbs without an existing elderly care unit. Also, the other criteria are to look for convenient and economical suburbs. A suburb with public libraries, fresh markets, police stations, recreational groups, and tram stops, etc. would fulfil this criteria. Hence, the cluster with more '*yes's'* in Table 4 was considered. It is noted that in Table 4 the number of *yes's* (left-hand side) is more for cluster 1 i.e. the red coloured clusters. Therefore the combination of *no* elderly unit values and red cluster instances was considered.

As seen in Figure 2, on the *no* (right-hand) side of the graph there are a few crosses marked in *red*, when double clicking on each of those (in WEKA), further details would be visible. The best alternatives were considered to closely fit the criteria.

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[1] Data pre-processing or scrubbing is a way of amending or removing incorrect, incomplete, improperly formatted or duplicated data from a data set. This can be done systematically by examining data for flaws using algorithms, lookup tables and rules.

Melbourne Suburbs	Males-65-69	Males-70-74	Males-75-79	Males-80-84	Females-65-69	Females-70-74	Females-75-79	Females-80-84	Elderly Care Unit	Public Libraries	Fresh Markets	Police Stations	Recreational Groups	hospitals	Shopping Centres	Tram stations	Bus Stops	Suburb ranking based on livability
abbotsford	1725	1244	1021	779	1691	1306	1141	983	yes	yes	yes	yes	no	no	no	no	no	53
aberfeldie	1013	875	703	453	995	875	787	641	no	no	no	no	no	no	no	no	yes	14
airport west	951	718	471	398	876	719	523	484	no	no	no	no	no	no	no	no	yes	228
albanvale	374	245	147	108	315	231	143	98	no	no	no	no	no	no	no	no	no	260
albert park	247	155	61	50	217	103	72	57	yes	yes	yes	no	yes	no	no	no	no	29
albion	223	167	116	102	191	165	118	97	no	no	no	no	no	no	no	yes	no	218
alphington	399	285	178	136	372	240	178	104	yes	no	no	no	yes	no	no	yes	yes	67
altona meadows	1121	965	815	557	1150	1088	1020	768	yes	yes	no	no	no	no	no	no	no	236
altona north	1121	965	815	557	1150	1088	1020	768	yes	no	no	yes	no	no	yes	no	yes	248
altona	1121	965	815	557	1150	1088	1020	768	yes	yes	yes	no	yes	no	no	yes	yes	184
ardeer	374	292	198	146	350	253	223	194	yes	no	no	no	no	no	no	no	no	244
armadale	119	86	60	56	124	86	53	47	yes	no	no	no	no	no	yes	yes	no	3

Table 3: Sample dataset

```
Cluster centroids:
                                              Cluster#
Attribute                                            0            1            2            3
                                                 (245)         (84)          (1)         (82)
========================                  ============================================
Melbourne Suburbs                          abbotsford   abbotsford     kalorama  alphington
Elderly Care Unit                                  no          yes           no         yes
Public Libraries                                   no          yes           no          no
Fresh Markets                                      no          yes           no          no
Police Stations                                    no          yes           no          no
Recreational Groups                                no          yes           no          no
hospitals                                          no           no           no          no
Shopping Centres                                   no           no           no          no
Tram stations                                      no          yes           no         yes
Bus Stops                                          no          yes           no         yes
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Table 4: Centroids of the Clusters formed

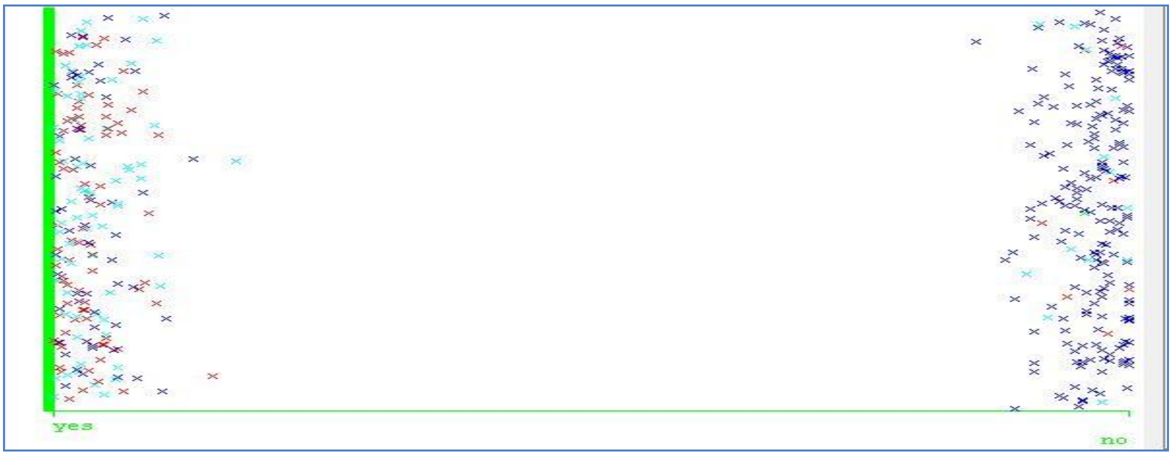

Figure 2: Elderly care unit vs Melbourne suburbs

In our study we have selected Warrandyte, Williamstown and Doncaster East as the suburbs that best fit our criteria. The details of all the three suburbs are shown in Table 5. The three alternatives Warrandyte, Williamstown and Doncaster East were scored against each cognitive element. A weighting of 8 was given to *vision* for Warrandyte as this suburb meets most of the goals. Williamstown and Doncaster East were given 5 for *vision* each as they only satisfy few of the goals considered. Likewise, *intuition*, *expertise* and *emotion* were also weighted for each alternative.

List Of Alternatives		
Melbourne Suburbs: warrandyte	Melbourne Suburbs: williamstown	Melbourne Suburbs: doncaster east
Males-65-69: 1930.0	Males-65-69: 563.0	Males-65-69: 91.0
Males-70-74: 1417.0	Males-70-74: 417.0	Males-70-74: 76.0
Males-75-79: 1153.0	Males-75-79: 322.0	Males-75-79: 45.0
Males-80-84: 1184.0	Males-80-84: 307.0	Males-80-84: 34.0
Females-65-69: 1911.0	Females-65-69: 545.0	Females-65-69: 74.0
Females-70-74: 1583.0	Females-70-74: 442.0	Females-70-74: 61.0
Females-75-79: 1336.0	Females-75-79: 354.0	Females-75-79: 43.0
Females-80-84: 1359.0	Females-80-84: 349.0	Females-80-84: 23.0
Elderly Care Unit: no	Elderly Care Unit: no	Elderly Care Unit: no
Public Libraries: yes	Public Libraries: yes	Public Libraries: yes
Fresh Markets: yes	Fresh Markets: yes	Fresh Markets: yes
Police Stations: yes	Police Stations: yes	Police Stations: yes
Recreational Groups: no	Recreational Groups: no	Recreational Groups: no
hospitals: no	hospitals: no	hospitals: no
Shopping Centres: no	Shopping Centres: no	Shopping Centres: yes
Tram stations: no	Tram stations: yes	Tram stations: no
Bus Stops: yes	Bus Stops: yes	Bus Stops: yes
Suburb ranking based on livability: 126.0	Suburb ranking based on livability: 40.0	Suburb ranking based on livability: 174.0

Table 5: Alternatives Selected

5.3 Phase 3

Based on the selected alternatives above, each alternative is weighted against each human cognitive element in the decision table by a decision maker. Table 6 shows the priority and weightage given for each element. The alternatives Warrandyte, Williamstown and Doncaster East are placed under the alternatives column. The human cognitive elements vision, intuition, expertise and emotion are placed as column headings as shown in the weighted decision table in Table 6. Further each cognitive element has its own priority column. The decision maker would prioritize these elements according to his/her choice and weight the suburb choices against each cognitive element considered on a 1 to 10 scale.

The test case example in Table 6 shows the four human cognitive elements considered - top priority was given to *vision* and the least priority given was for *emotion*.

COGNITIVE ELEMENTS --->		Vision		Intuition		Expertise		Emotion	
	Priority	4		2		3		1	
ALTERNATIVES									**SCORE**
Choice 1: Warrandyte		8		6		5		5	64
Choice 2: Williamstown		5		3		7		3	50
Choice 3: Doncaster East		5		5		7		2	53

Table 6: Weighted Decision Table

The final scores were calculated. The final score for Warrandyte was 4*8+2*6+3*5+1*5=64, Williamstown: 4*5+2*3+3*7+1*3=50, and Doncaster East 4*5+2*5+3*7+1*2=53. To conclude, the scoring was done for each alternative keeping the decision criteria in mind. Hence, for the criteria: there shouldn't be any elderly care units in the area; the suburb should be convenient; and it should be economical and viable to construct a unit in the particular suburb – the best suited suburb in Melbourne to start an elderly care unit was *Warrandyte* with the highest score 64 as shown in Table 6.

6 DISCUSSION AND CONCLUSION

In this section, we reflect on the research question identified in Section 1. *How can organizational decision-making be improved using human cognition and machine intelligence?* In addressing this question, we designed a new IDSS methodology that embedded human cognition and 'clustering' as a data mining technique to sift out useful patterns and trending information.

This new IDSS methodology incorporated in a decision support system, takes us through a three-phased approach for effective decision-making. Phase 1 emphasizes the phrasing of the decision considering all the criteria by the decision-maker. Phase 2 uses the *machine* to analyse the huge volumes of data available through *clustering*, a data mining technique. At the end of Phase 2, decision makers would be able to select several alternatives based on his/her decision-criteria. Phase 3 involves human cognition elements. All the alternatives are weighed against human cognitive elements in the decision matrix and the best alternative is selected.

Can our new methodology that combines data mining technique and human cognition assist managers to sift through large data sets and be able to make easy, relevant and timely decisions with little or no IT technical knowledge? Based on the tests we conducted as discussed in Section 5, we were able to extract and deduce *sensible* and *relevant* information for decision-makers using this new methodology in an aged-care context using large datasets from the Victorian websites.

Does the consideration of both human cognition elements and data mining technique on large data sets provide us with useful information to improve decision-making? Early evaluations of our methodology as a prototype provide support that our automated approach that includes human cognition elements and clustering, can be used by decision makers with little or no knowledge of using complex data mining systems to sift through large amounts of data to make effective and timely decision.

Is the resulting methodology useful as a decision-making tool for managers in organizations? Our initial testing and evaluation of the methodology on a large data set on elderly care units in Melbourne suggest that the embedded human cognitive elements within this proposed DSS methodology can successfully be used to reduce the size of large data sets into meaningful information. Our initial findings also indicate that there are other important cognitive factors: tacit knowledge of the decision-maker, a deep knowledge of the data set(s) and knowledge of the decision-making context and environment influence the decision-making process.

This study is a part of a larger research in progress project. The approach developed in this study provides a systematic step-by-step methodology for designing an improved IDSS. One limitation is that the system is not fully implemented and ready to be hosted. Future scope of the research is to follow this proposed methodology and implement a whole new fully automated application including a user-friendly GUI. Furthermore, future work includes: (1) testing and validating human cognitive elements in decision-making in organizational settings with formal ethics approval using comprehensive interviews, and (2) making use of other data mining techniques such as regression, classification, summarization, constraint clustering, and (3) evaluation of the methodology in different organizational contexts.

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