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Procedia - Social and Behavioral Sciences 00 (2014) 000–000

Procedia
Social and Behavioral Sciences

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Marketing decision support using Artificial Intelligence and Knowledge Modeling: application to tourist destination management

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Abstract

Knowledge-based information systems are advanced tools in the hands of the marketer, enabling him to take evidence-based decisions in complex situations. In this paper, advanced data analysis, neural networks and knowledge representation technologies are brought together towards an intelligent information system for tourist destination marketing. In previous work, knowledge engineering methods were proposed for the extraction and modeling from market survey data of factors, associations, clusters and hidden patterns that explain a market phenomenon or customer behavior. The feasibility of managing these findings in a Knowledge-Base, as reusable, sharable and machine understandable knowledge was shown using preliminary results from primary surveys on the tourism of Thessaloniki. In the current work, we present the continuation of these developments, including: (a) the final results of the survey on the tourism of Thessaloniki, (b) a refined Knowledge Base filled with real and validated content derived from the analysis of the full-scale survey data, (c) the extension of the methods with an artificial neural network classifier and (d) the deployment of an inference engine and a query mechanism in order to exercise the knowledge content for decision support. Pilot trials showed that the intelligent system was able to assist users who are not experts in analysis to solve typical destination marketing problems.

Selection and peer-review under responsibility of the 3rd International Conference on Strategic Innovative Marketing.

Keywords: Decision support; tourist destination marketing; neural networks; intelligent systems; multidimensional data analysis; Thessaloniki;

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1877-0428
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1. Introduction

In the recent years there is a tendency to exploit the huge amount of data available within modern information systems or exchanged through the web, in order to perform evidence-based marketing. Terms such as data mining, data analytics, predictive modeling and big data refer to technologies that are evolving rapidly and have become powerful tools in modern marketing and many other business activities (Bouset, 2007). These techniques can be now considered as widely accepted and mature, since there are a large number of companies offering specialized software, data analytic services and training to intelligent techniques based on data analysis. However, it is also true that the task of extracting essential information from data and performing marketing tasks based on intelligent techniques requires specialized skills and often a background in information technology (Schreiber, 2008). On the other hand, the well-established questionnaire-based primary surveys remain a fundamental source of information. Considering the cost of these surveys, it is desirable to extract the maximum possible useful information from the acquired data by applying advanced analysis techniques, to consolidate results from different surveys and to generalize the findings so that they are reusable in similar problems.

Informed and intelligent decisions in managing tourist destinations is a challenging field, since many factors are involved, such as culture, branding and communication (Kavoura & Bitsani, 2013), as well as many opportunities for actions by authorities and DMOs (Kavoura, 2013). Considerable efforts have been reported in developing decision support systems for tourist management, based on information management technologies (Bouset, et al, 2007), knowledge management systems (Prantner et al, 2007) and other intelligent approaches such as statistical forecasting (Haiyan, Bastian & Vera, 2010). In our previous work (Stalidis & Karapistolis, 2013), we proposed a data analysis and knowledge management framework, where specialized statistical analysis methods (Benzecri, 1992) were applied to survey data and the results were model as knowledge that could be stored in a Knowledge Base and used by a marketer through an intelligent system to receive answers to queries on marketing decision problems. The expected benefits were that the knowledge accumulated in a Knowledge Base (KB) can be used through intelligent decision support tools to provide solutions to complex problems, without requiring expertise or deep knowledge in data analysis and interpretation by the user. Another important benefit was that knowledge is maintainable, expandable and easier to consolidate existing with updated one, unlike data which are usually not reusable. Finally, it is worth mentioning that by adopting the appropriate formalism, knowledge can be exchanged between systems and accessed through the semantic web, so that instead of requesting data from a database, it is possible to request intelligent answers to high level questions.

In the current paper, we present the continuation of this work with recent system developments, application to tourist destination management and the expansion of the approach with an automatic classification component based on artificial neural networks (NN) (Simpson, 1990). In the following section, the extended overall scheme is presented and in Section 3 the results of the survey on the image of Thessaloniki, the data analysis and the extracted knowledge content. In Section 4, the application of the NN classifier is illustrated, while in Section 5 the operation of the query-based decision support tool are shown. Conclusions and future work are presented in Section 6.

2. Background and methods

2.1. The overall analysis and artificial intelligence scheme

The methods presented in this paper consist of three main parts, integrated into an overall data analysis, knowledge engineering and intelligent decision support scheme. Firstly, the Data Analysis component includes a set of explorative statistical analysis methods from the family of multidimensional factor analysis (Benzecri, 1992) and is aimed at the identification of multivariate nonlinear relations among variables, the decomposition of complex phenomena into factors and the identification of population clusters and their distinctive characteristics (Greenacre, 2007). Secondly, the Neural Network component is trained to generalize the classification of cases into known classes, so that an intelligent decision can be taken automatically about a new unknown case based on the acquired knowledge (Morajda, 2003). The Knowledge Modeling part supports the ability to express the results of data analysis in a machine understandable form and to handle them in a Knowledge-Based System (KBS) (Schreiber, 2008). These three parts consist a Tourist Marketing Decision Support system (TDSS) based on knowledge extraction and engineering. The overall scheme is illustrated in Figure 1.

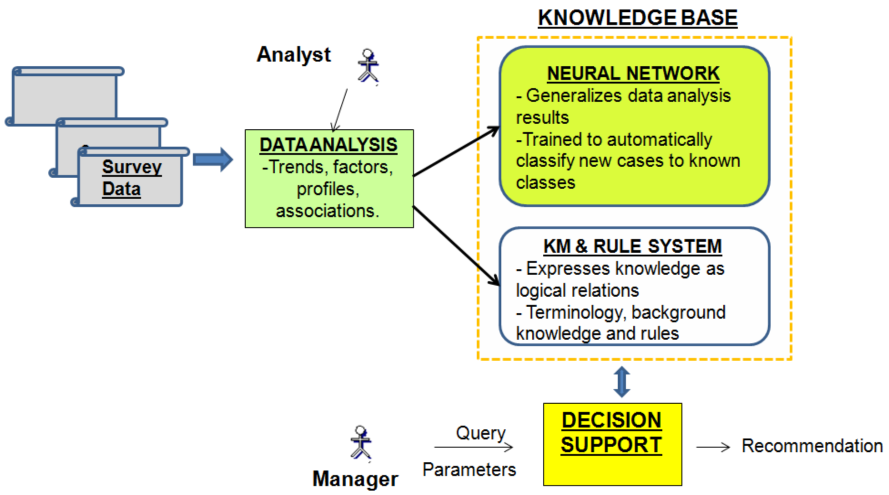

Fig. 1. The overall data analysis, knowledge engineering and decision support scheme

The Data Analysis component plays the role of knowledge extraction, it is addressed to the Analyst, who is responsible for acquiring the survey data, performing specialized explorative analysis and providing the results, initially in standard human understandable form. The data analysis is performed using explorative factor analysis methods and in particular a combination of Multiple Correspondence Analysis (MCA) and Hierarchical Clustering (CAH) (Benzecri, 1992). The specific methods were selected as particularly suitable for revealing underlying patterns, such as customer profiles, market segments and product features that match specific demand and at the same time perform well with the relatively small datasets that are typically acquired from questionnaire-based surveys.

The most critical element in the Knowledge Engineering part is the Knowledge Model (KM), that is to define the knowledge structure, terminology and formalism, so that the model is able to express in an effective way the entire logic and content (both background and domain knowledge) that is sufficient for problem solving by an intelligent engine (Guarino, 1995). The KM is implemented within a Knowledge Base, which is the container of the produced knowledge and the operational component used to maintain and retrieve it. Another important element in the proposed scheme is knowledge elicitation which is performed by human experts with experience in analysis and involves the interpretation of analysis results, the selection of those findings that are useful for decision support and rejection of those that are not meaningful, as well as the process of transferring these findings to the rule syntax defined by the KM.

A component for classification and pattern recognition based on neural networks (NN) has been developed and linked with the data analysis component. The aim was to automatically classify unknown cases under study, such as visitors or services, for which analysis has not been performed, into groups/patterns, based on the mapping that resulted for similar cases from the data analysis. This process would be typically performed by an experienced analyst using classification methods from the same family as the clustering and factor analysis methods mentioned above. In order to automate this process, we take advantage of the ability of NNs to be trained on a limited training set and then generalize the knowledge to respond to similar but unknown problems (Simpson, 1990). In this project, a Back-propagation NN (Chen, 1994) was trained to classify visitors according to their image attributes to representative types of visitors that have been discovered during the data analysis process.

The Decision Support component is addressed to the marketer/manager and consists of a user interface that receives and responds to queries and an inference engine, which is able to use the accumulated knowledge and input parameters, to run logical rules and to answer high-level questions on marketing planning issues. The Marketer has thus access to the consolidated analysis results but not to the original data, in order to address a range of marketing problems, including the optimal positioning and promotion of tourist destinations, identification of trends, market segmentation and assessment of competition.

The development of the KM, the implementation of the Knowledge Base and the decision support mechanism, were performed in the Protégé-OWL 4.2 platform (Protégé, 2014), adopting the OWL-DL (Description Logic) sublanguage (OWL, 2014), which support semantic definitions, incorporation of logic and is suitable for exchanging knowledge through the semantic web. The SWRL (Semantic Web Rule Language) (SWRL, 2014) was also used to compile rules

2.2. Neural Networks

The use of Neural Networks in artificial intelligence has a history of several decades (Rosenblat, 1958). Passing through phases of enthusiasm, disillusionment and maturity, Neural Network technology has proved its ability as a knowledge extraction and representation tool in a wide range of fields, including business intelligence (Lisboa, 2001), economics (Morajda, 2003) and biomedical engineering (Strintzis, 1992). Neural Networks are based on the concept of imitating the function of the human brain, offering features such as generalization from samples and supervised or unsupervised training. In practice they are non-linear statistical data modeling or decision making tools that can be used to model complex relationships between inputs and outputs without the need to explain the underlying phenomena (Simpson, 1990). NNs are applicable to almost all problems where the goal is to represent a relation between predictor variables (independent or input variables) and predicted variables (dependent or output variables), especially when this relation is too complex to be considered as association or clustering. NNs are able to learn through examples and to model non-linear relations among multiple variables, without nevertheless providing any explanation or human understandable rules. For this reason, they do not seem useful as analysis tools and are unable to contribute to theory generation, however they are successful in automatic decision making and non-linear classification.

3. Analysis of survey data and knowledge elicitation

The input data for this study were collected through a primary survey launched in the city of Thessaloniki. The instrument was a 3-page structured questionnaire containing 43 questions, organized in 8 sections, including questions regarding the visitor’s familiarity with the destination, his general satisfaction and future stance, the reasons for choosing this destination and factors influencing this decision, a number of attributes related to the perceived image of the city and the country, as well as personal/demographic information. The aim of the survey was to collect information on the perceived image of the city of Thessaloniki, as obtained by visitors during their visit, to study their expectations and decision factors and to analyze the factors contributing to their needs and satisfaction. The survey was addressed to foreign visitors of the city, who in many cases were visiting Thessaloniki on their way to their main vacations in nearby locations, usually beach areas in Halkidiki or Pieria. The sample was 1947 tourists, collected during the period from May to October 2013.

The sample consisted of 46, 1% men and 53,9% women, 5,85% were below 8 years old, 45,9% were in the age category 19-35, 22,7% were from 36 to 45 years old and 26,9% were 46 and above. The purpose of their visit for 75% of the sample was vacation, while 7,9% came for professional reasons, 4,9% for shopping and the rest for other reasons. The large number of countries of origin were divided into 15 groups, with most important ones the Balkans (15, 15%), Russia (13, 10%), UK (12,48%), Germany (11,40%), Northern Europe (9,98%), Central Europe (7%), France (6,98), Italy (6,21%) and others with smaller representation.

In the section “Reasons for choosing this destination”, the visitors were asked to select their first and second priority among 5 options to the (a) reasons that affected you in visiting this city, (b) elements that mostly attracted you during your visit and (c) factors that you consider as the most important for selecting a destination. The most popular reason for visiting Thessaloniki (Figure 2) was its history (selected by 44,4% as 1st or 2nd choice) and visits to museums (42,77%) and beaches & swimming (41,39%). In question (c), the most important factor in a destination was considered the natural environment (57,15%) and the least important the local transports (19,2%).

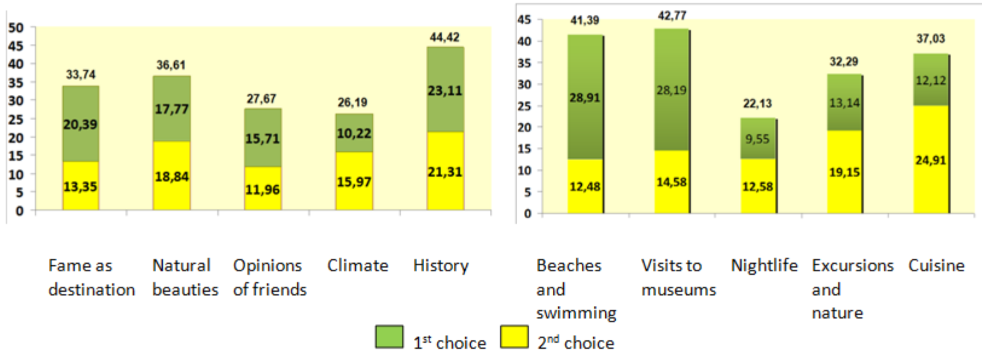

Fig. 2. The visitor responses regarding (a) the most important decision factors that influenced them to select this destination (b) the most attractive elements during their visit.

The analysis of the above section using a combination of MCA and the VACOR algorithm (Benzecri, 1992) resulted in 5 classes of visitors with the following characteristics and estimated size: Class Γ1 (14,8%): Attracted by visits to museums, Class Γ2 (17,4%): Attracted by nightlife and lifestyle, affected by opinions of friends, Class Γ3 (12,5%) Attracted by nightlife and lifestyle, affected by advertisements, Class Γ4 (21%) Attracted by beaches and swimming, affected by fame as destination and climate, consider cost as important, Class Γ5 (34,3%) Attracted by excursions & nature, affected by natural beauties, climate (2nd choice), and consider as important the environment and lifestyle (2nd choice).

Within the responses for the 9 items on the image of Thessaloniki, the most negative evaluations were for Cleanness (52,3% negative or neutral), while the most positive ones were for Greek cuisine and friendliness of local people (both around 75% positive or very positive). The factor analysis (MCA) showed that there was an overall escalation from negative to positive responses and revealed 5 classes. The most negative standpoint was class A, characterized by negative image for sightseeing, Greek cuisine and friendliness of local people, and next were Class B characterized by negative image for prices and security and Class C by negative image for natural beauties and city style. Class D corresponded to neutral image for all items but negative for cleanness and Class E to positive image overall. Class D was associated to 32,3% of the respondents while Class E to 31%, meaning that about one third of the visitors obtained a fully positive image, one third were neutral without any particular element standing out apart from the negative image for cleanness and one third were visitors with noticeable negative image in 3 different categories of elements.

The clustering of visitors in terms of the frequency and duration of their visits, country of origin and general view on their experience from the city indicated the following classes: (a) Visitors from France, Italy, Russia and Spain, whose visit in Thessaloniki lasted 1 week and they were clearly positive regarding the cost of the trip and their general experience. (b) Visitors mainly from the Balkans and counties of South-Eastern Mediterranean, who stayed in Thessaloniki for 1 or 2 days and had no other significant characteristic. (c) Visitors from Eastern Asia, Australia, North America and Central/South America, who came for the first time to the country or have not visited the city for the last 5 years. (d) Visitors from UK, Germany and other Central Europe countries, who are frequent visitors of the city and their stay lasts for more than one week. Their opinions regarding the cost and their experience did not differ from the mean and they are considered as the regular tourists who visit the city during their summer vacations in the nearby beach areas. (e) Visitors from Central Europe and former Soviet republics, who have visited the city or the country at least once before and their opinion regarding the cost and their experience was neutral or negative.

After completing the above analysis process for selected sections separately, the next step was to apply MCA on the full set of class membership variables in order to observe an overall picture of their dependencies, together with the effect of demographic variables. More complex relations were found regarding which decision factors are considered more important and which characteristics of the city worth emphasizing depending on the culture, character of visit and priorities of specific customer groups. The above results were converted to rules, expressed according to the formalism of the developed KM. The KM and the rule formation process were developed in previous work (Stalidis & Karapistolis, 2013b) and were based on ontologies and the Ontology Web Language (OWL). The ontology (Ou et al, 2008) provided a description of the domain of interest, which included definitions of concepts, objects or individuals, classes (i.e. types of objects), relations among them and properties, while a rule-based component was added to express more complex logical relations and operations. The process of updating the model and introducing content into the Knowledge Base was performed at the following 3 levels:

1. The ontology contains the basic definitions of the tourist marketing domain and special classes to express findings of the analysis, such as visitor profiles, e.g. types of visitors according to their destination image: NegativeWithIdentity, NegativeWithPractical, NegativeWithStyle, NeuttralImage, PositiveWithAll, PositiveWithCulture, Similarly, classes of visitors were defined according to their image for the country, to their decision priorities, to their nationality and culture, and whatever structure has been found by the analysis in the primary data.
2. Properties were used to express relations between objects and to assign specific values to object attributes. E.g. *myvisitor* isFrom *Italy*, *myvisitor* hasAge 30, *myvisitor* IsA *VisitorForSeaside* are property assertions relating an individual visitor with a specific country (is from Italy), defining his age and classifying him in a special category of visitors who are mainly interested in beaches & swimming.
3. Rules are used to formulate knowledge in the form of predictions or suggestions, which are estimated given a set of conditions and input variables, e.g. a finding from the factor analysis relating image, purpose of visit and the reason for selecting the destination was that “if a visitor is young and his purpose of visit is vacation, a first priority decision factor is nightlife”. Rules were distinguished as intermediate rules, used to give properties if some conditions are met, or as main rules if they provide a prediction or conclusion.

The outcome of the rule formation process for the survey performed on the image of Thessaloniki was at the current stage 80 intermediate rules, 73 main rules and 19 analysis-based composite class definitions.

4. Neural network classifier

The NN is linked to the overall system functionality in two ways, the process of training and the process of classification (or recall). In the process of training, a large number of classification examples, which are derived from data analysis and are considered as correct, are given as training data to the NN. These data consist of an input table and an output table, where the rows of the input table contain the values of input variables for different cases (i.e. the answers of respondents in a particular questionnaire section) and the rows of the output table contain the corresponding target value of the output variable(s). A typical example is that the input table may contain the demographic data and the responses regarding the purpose of their trip and their main requirements of a large number of survey respondents. The output table would contain the class in which each respondent has been classified by cluster analysis on the basis of the input variables (e.g. visitor for shopping, visitor for vacation, etc.). The classification or recall process can only be performed after the successful completion of the training process and is part of the decision support functionality. A vector containing the values of the input variables for a new unknown case is fed into the input layer of the NN and the resulting output is used as an estimation of the class in which this case belongs. The decision provided by the NN is expected to replicate the classification result that would be produced for this case by the VACOR algorithm, if the case was included in the data analysis. The achievement is that a new unknown case can be classified by the system using the already captured knowledge without the need of repeating the analysis and taking advantage of the generalization abilities of the NN and its insensitivity to partial input data.

Table 1. Classification of visitors to 3 classes based on their destination image . MSE= 0.165, correctly classified instances: 85.9%..

MSE = 0.1648		Predicted class		
		K1	K2	K3
Actual class	K1	6 (66.6%)	4 (9.7%)	0
	K2	3 (33.3%)	33 (80.1%)	0
	K3	0	4 (9.7%)	28 (100.0%)

In our experiments, Factor Analysis was applied on the variables regarding the image of Thessaloniki in order to reveal the main factors explaining their views and to identify representative classes of visitors in terms of their image, followed by the VACOR algorithm to classify the visitors into corresponding groups. Two classification cases were produced, the first one allocating respondents to 3 classes and the second case to 5 classes. A separate NN was trained and evaluated for these two cases. The input table contained 390 cases and was randomly partitioned to data assumed as known (training data) and data unknown (testing dataset) using cross-validation. The proportion of the train and the test set was 80% - 20%. The classic back propagation neural network (BPN) technique was chosen to train the NN. This technique is based on the principle that any mistakes made by the network during training, get sent backwards through it in an attempt to correct it and so the network is progressively learning what’s right and wrong. In our application, the BPN consisted of a single hidden layer and the number of its hidden neurons was 5 to 10, selected according to the complexity of the problem, in order to optimize performance and avoid over-fitting. Monte Carlo simulations showed that when the number of hidden neurons was rising, the prediction error and the training time also increased. As for the other parameters of the NN, the value of momentum was 0.75 and the learning rate 0.05.

The classification results were evaluated through the confusion matrix and the Mean Squared Error (MSE) (Table 1).When visitors were classified into 3 classes, the NN performed better than the 5 class case. For the first classification case, 80.1% and 100.0% respectively, of instances of classes K2 and K3 were correctly predicted and the overall agreement reached 85.9% with MSE=0.1648. As for the second case, only in classes K1 and K5 we had almost no false classifications from the test set (agreement of 94.4% and 100.0% respectively), while the total agreement reached 67.9% with MSE=0.3270. These results confirm that the NN can learn how to generalize the results of data analysis in a multidimensional classification problem. However, they also point that if the visitors are categorized into less and larger groups, the NN is more easily trained, while as the decision becomes more complex it performs with more limited success.

5. Decision support

The knowledge content can be exploited by a marketer for decision support via a query mechanism. This mechanism is supported by an inference engine (or reasoner) which applies logic to the declared knowledge in order to compute query results. The Protégé-OWL 4.2 environment includes preinstalled reasoner engines and a DL-Query tab for querying the ontology with OWL-DL expressions. These mechanisms were used to solve problems such as to get suggestions about the most critical decision priorities of certain target customers, to estimate the size of specific market segments, to predict the possibility that a visitor with selected characteristics repeats his visit or to find opportunities for cross-selling tourist products.

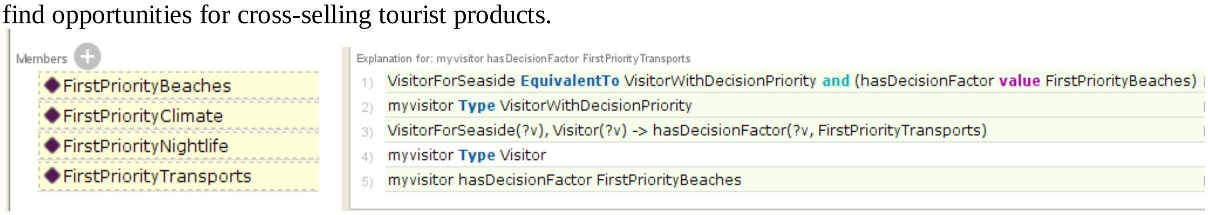

Fig 3. (a) The properties inferred by the engine for the visitor. (b) The explanation for the visitor’s property “first priority transports”.

To ask the question “which are the first priority decision factors for a visitor who comes from Italy for swimming/seaside vacations and is in the age category 56-65”, an individual visitor was created, named myvisitor and he was given the properties hasAge *Age56-65*, isFrom *Italy*, hasDecisionFactor *FirstPriorityBeaches.* After activating the inference engine, an OWL-DL query gave the decision factor properties related to our target. It came out (as shown in Figure 3a) that *myvisitor* was classified as VisitorForSeaside and was linked with FirstPriorityTransports, FirstPriorityNightlife, FirstPriorityClimate, which means that according to the rules in the system, the specific type of visitor is predicted to seriously consider nightlife, the climate and the quality of transports. By clicking on e.g. FirstPriorityTransports, the system provides an explanation why it inferred the specific property (Figure 3b). In a similar way, additional queries were applied to find which individuals have a specific property (e.g. what type of visitors are interested in low-budget vacation, etc.).

6. Conclusions

In this paper we present recent developments of previous work on an intelligent data analysis and knowledge modeling framework for marketing support in the tourist sector. A new intelligent component was added to the developed system based on Neural Network technology to provide automatic classification of unknown cases without performing new data analysis but by generalizing the knowledge derived by already analyzed examples. This process can be conceived as a secondary knowledge extraction process, where the knowledge extracted from data using statistical analysis was crystallized and generalized by a second modeling mechanism. The results of this experiment were encouraging, since the NN managed to classify unknown testing patterns with acceptable accuracy. Our plans for future work include the training of the NN(s) to additional decisions based on a large set of input variables and the testing of the results with additional survey data.

Acknowledgements

This research has been co-financed by the European Union (European Social Fund – ESF) and Greek national funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF) - Research Funding Program: ARCHIMEDES III.

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