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Improving Intelligent Decision Making in Urban Planning:
Using Machine Learning Algorithms

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ABSTRACT

Generally, decision making in urban planning has progressively become difficult due to the uncertain, convoluted, and multi-criteria nature of urban issues. Even though there has been a growing interest to this domain, traditional decision support systems are no longer able to effectively support the decision process. This paper aims to elaborate an intelligent decision support system (IDSS) that provides relevant assistance to urban planners in urban projects. This research addresses the use of new techniques that contribute to intelligent decision making: machine learning classifiers, naïve Bayes classifier, and agglomerative clustering. Finally, a prototype is being developed to concretize the proposition.

KEYWORDS

Clustering, Data Mining, Intelligent Decision Support System, Machine Learning Algorithms, Naïve Bayes, Urban Planning, Urban Project

INTRODUCTION

Formerly, people lived and worked mainly in rural areas. Nowadays the world has changed; and the cities are spreading to new territories. This phenomenon of urban sprawl is largely due to the disorganized management of urbanization by the concerned states, particularly, in the developing countries (Knox, 2016). Hence, it has led to messy urban situations.

Urban planning treats this kind of problem, but it is still one of the most complex domains that you could make a decision because of including many actors and the multi-criteria nature of spatial problems (Laurini, 2001). On the one hand, several conflicting criteria (Massam, 1988) are often taken into account in evaluating different planning processes, which present a problem of reaching a compromise with regard to a solution that satisfies all participants. On the other hand, there are projects that seem good for urban planners, but the citizens express their dissatisfaction.

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In addition, the huge quantity of data that have increased rapidly cannot be managed by frozen standard tools. Therefore, traditional systems are no longer able to assist decision-makers. In recent years, many methods, models and systems have been developed. They are scanty, deficient and cannot scope the intricacy of these problems. Consequently, we suggest an intelligent system to deal with the cited problems, using combination of machine learning algorithms.

The remainder of this paper is organized as follows. The problem statement and our goals are both described in Section 2. The related works are presented in the third section. Section 4 includes detailed description and subsystems, the proposed system's architecture. Section 5 presents our case study. Section 6 summarizes the results of this work, draws conclusions and points to future research.

PROBLEM STATEMENT AND GOALS

Nowadays, the population, around the world is largely urban. More than half of them live in urban areas, so the growth of the population has accelerated, which has resulted in negative consequences, rather than positive ones: new aerated towns and cities are proliferating. In this case, public authorities should apply solutions.

As a bearer, facilitator and guarantor of the planning and implementation process, they are supposed to guarantee to minimize this development, which is carried out informally, as well as guarantee the continuance of the development by following an urban planning strategy.

Urban planning process ends up with an urban project that should be realized, and every urban project needs a hosting site. Hosting site choice represent the last phase in urban planning process before the realization take place. Specialists consider this phase as one of the most complex parts in the whole process. Several aspects in this phase may come in as decision factors: politics, socioeconomic, cultural, religious and other; especially, when we talk about taking account of civil society actors.

We choose the field choice problem (case study), which is a multi-sectoral problem that includes dozen of administrations in agriculture, town planning, public works, etc. The participating entities must give their opinions on the proposed site, where each of them has its constraints and easement. Each field has its own characteristics, such as the nature of land (agricultural, clayey...), underground installations (electricity cables, telephone cables, gas lines ...). The Planning group must decide which site will host the project from the proposals.

The obvious impediment of today‘s urban development is due to the weak decisions, and the citizens' dissatisfaction of the realized projects. The citizens' contentment represents one of the prerequisite principles of a sustainable development, which also remains a big problem.

Therefore, the group must make a decision that meets both decision makers' objectives and the citizens' objectives. Despite the fact that considerable attention has been paid to this domain, public authorities suffer from a fatal shortage in planning tools.

Goals

The main objective is to propose and develop an intelligent decision support based on novel methodology, which can help decision makers formulate and select the optimal strategy. The system can autonomously learn, perceive without external supervisory intervention and change its behavior from a use to another. It acquires from previous uses to increase the performance of decision support, which is dedicated to the decision makers. We offer a decision support, not through the MCDA methods, but rather through the use of other techniques and tools. The next section discusses some related works.

Literature Review

For several years, great effort has been devoted to the study of decision support in urban issues, where sundry decision support systems (DSSs) (Power, 2002) and intelligent decision support systems (IDSSs) have been realized. These systems usually use multiple criteria decision aiding (MCDA) methods (Roy, 2005) and artificial intelligence (AI) techniques. The IDSSs are based on prediction and decision models that analyses huge amounts of variables to solve a problem (Aronson, Liang, & Turban, 2005 ; Kaklauskas, 2015). Several publications have appeared in recent years presenting DSSs and IDSSs dedicated to urban issues. (e.g., Benatia, Laouar, Eom & Bendjenna, 2016; Benatia, Laouar, Bendjenna & Eom, 2015; Chichernea, 2014; Velasquez & Hester, 2017; Chakhar & Mousseau, 2009; Laouar, 2005; Asadi & ghatee, 2015; Kar, 2015; Khediri, Laouar & Eom, 2019; Zhou, Noble & Cotter, 2015; Coutinho-Rodrigues, Simão & Antunes, 2011; Park & Stenstrom, 2008; Ofli, Meier, Imran, Castillo, Tuia, Rey, Briant, Millet, Reinhard, Parkan & Joost, S 2016; Moghadam, Delmastro, Khediri & Laouar, 2018a; Khediri & Laouar, 2018b; Lombardi & Corgnat, 2016; Iskin, Daim, Noble & Baltz, 2014; Laslo & Gurevich, 2000).

Cloud-based DSS In order to reduce enrich the communication and the cooperation between the decision makers in the process of selecting best urban project, a Cloud based DSS is developed (Benatia, Laouar, Bendjenna & Eom, 2016). The cloud-based DSS is deployed on a platform Cloud (CloudBees) and includes the multiple criteria decision making (MCDM) method PROMETHEE II. The authors affirm that proposed Cloud based multiple criteria DSS has other significant advantages such as reducing the deployment time and the cost.

Smart City Development DSS In the context of a smart city development project, there are ample researches exploring decision issues in general. Chichernea (2014) considered the components of a decision support system as a necessity for the development of a smart city and/or smart home due to the strategic, tactical and operational assistance offered by this tool. Aiming to treat particular urbanization issues, Rienow and Goetzke (2015) combine the simulation skills of cellular automata (CA) with support vector machines (SVM). This combination permits the dynamical simulation of diverse growth types besides the analyses of various geophysical and socio-economic driving forces.

Urban Infrastructure Planning DSS Some researchers integrated GIS as a primary component in their DSSs. A DSS, MCPUIS (Multicriteria Planning of Urban Infrastructure Systems), is presented to support planning the urban infrastructure (Coutinho-Rodrigues Simão & Antunes, 2011). The MCPUIS includes GIS as a crucial element that facilitates the process of evaluation. MCPUIS includes also three MCDA methods: SAW (Simple Additive Weighting), TOPSIS (Technique for Order Preference by Similarity to Ideal) and ELECTRE I, which fit in the ELECTRE (Elimination and Choice Translating Reality) (Roy, 1990).

Industrial Sites Classification DSS Rikalovic et al. (2017) introduced a new intelligent decision support system to classify industrial sites using a geographic information system (GIS), expert knowledge, and machine learning techniques. This system generates alternatives locations based on a geographic information system, and classify sites using a hierarchical neuro-fuzzy approach and a knowledge base. This proposed system provides precise results for industrial site classification at the local level, according to real-world problems experimentation.

Because of the continuing trend of urbanization fundamental problems of mitigating local and global pollution have still to be addressed. in addition to the present-day stock, which is characterized by low energy performances, an integration of building simulation (BS) approach, multi-criteria analysis (MCA) methods and geographic information system (GIS) tool for developing a new multi-criteria spatial decision support system (MC-SDSS) in urban context is possible (Moghadam, Delmastro, Lombardi & Corgnat, 2016).

Urban Lighting Management DSS A proposition of massive data based on intelligent decision support system is presented to help both the government agencies and corporate business in advanced planning, collaboration and management (Zhou, Noble & Cotter, 2015). In the same context, Chen et al. (2015) proposed an IAMSULI (Intelligent Analysis and Mining System for Urban Lighting Information) that aims at providing better decision support for lighting management.

Urban Transportation Management DSS Asadi and Ghatee, (2015) developed a rule-based decision support system (RB-DSS) to estimate the accident frequency and severity for different scenarios of transportation. RB-DSS is designed to find the safest solutions for routing, scheduling, and assignment in Hazmat transportation management. Some other research utilized muti agent system (MAS) to responds to the system's intelligence. In order to create new programs for traffic controllers, Iscaro and Nakamiti (2013) presented a supervisor agent for urban traffic control, which includes fuzzy sets, genetic algorithms and case-based reasoning.

Urban Land Use Planning DSS Park and Stenstrom (2008) investigated Bayesian networks to classify urban land use. They affirm that, for environmental issues, such as estimating storm water pollutant loads, this classification provided timely and inexpensive land use information over large areas (Laurini, 2001).

Ghavami et al. (2017) presented an intelligent planning support system for spatial urban land use planning, based on multi-agent systems. The proposed system include two principal phases: a pre-negotiation and an automated negotiation. In order to acquire the actors social preferences, the pre-negotiation phase imply interaction between human actors and the intelligent software agents. Actors' social preferences modeled by the agents, which used social value orientation theory rooted in social psychology. The aim of the study is to design socially rational intelligent agents who work on behalf of real actors, using a Bayesian learning technique effective in computing, as well as social value orientation theory. The proposed system is applied to real world urban land use planning, human actor participate in the prenegotiation phase and through a number of interactions their social preferences are aroused by intelligent software agents. The results of the study show the proposed system efficiency for automated negotiation.

Synthesis

The literature on DSSs and IDSSs for urban problems shows a variety of approaches, model methods and techniques. They have advantages as well as drawbacks or limitations, which are either the multiple-criteria decision analysis' methods, the integrated data mining techniques or several combined techniques.

Using MCDA Methods

The use of MCDA methods can lead to many possible disadvantages; for example, an incredible amount of input is necessary at every step of the decision process and outcomes can be hard to explain in layman's terms (Konidari, & Mavrakis, 2007). Such method does not provide a clear method to assign weights. Nevertheless, when we have a large number of criteria, the problem of comparisons expands (Velasquez & Hester, 2013).

Using Multi Agent Systems

The use of multi agent system responds to the concept of intelligence in system and it is considered as a very cogent tool, because agents are autonomous. However, they have many drawbacks. MAS may not be conventional in all situations, one of the main weaknesses of MAS is the heavy load, which is caused by communication among the agents, especially when we talk about huge volume of data; the amount of communication makes MAS out of control.

Using Machine Learning Algorithms and Data Mining Techniques

Generally, machine learning and data mining techniques are very powerful tools that can be used in decision support with some disadvantages. Data mining uses a wide range of techniques such as case-based reasoning, clustering analysis, classification, association rule mining, and data visualization (Johnson, 1967). Data mining could perfectly increase the "intelligence" of DSS and it has recently become a substantial component in designing IDSS (Yang, Tan, Li & Ruan, 2012).

The Proposed System's Architecture

In this section, we present the intelligent decision support system's proposed architecture, based on data mining and machine learning, with a description for its components.

The IDSS architecture comprised of the four modules as shown in Figure 1. Integrating internal process necessitates the use of naive bayes that represent a machine learning classifier and managing an external process of collecting data requires a database management system and an ergonomic user interface.

Database Module

The database represents an indispensable module in this architecture. We do not specify any type of databases to use (relational, non-relational, Not Only SQL (No-SQL), object oriented database, etc.) in order to individually allow the user (developer) to choose of the adequate type that fits his/her requirements because the urban planning has to deal with many issues such as transport, housing, water management, conservation and other others. Database, in our architecture, is axiomatically used to store the data (urban in our case). The nature of crucial urban data (required data for planning), is voluminous and massive and maybe heterogenic and unstructured (satellite images in the future of millions of streets). Considering the diverse nature of data in urban planning, the user of the this proposed system and methodology must think individually about a data base management system (DBMS) that has the ability to store this amount of data, so we neither specify the type of database nor the database management system (DBMS) to be used for processing the data.

Naïve Bayes Process

The first internal process is naïve Bayes. In this section we explain how we use it for the prediction.

Bayes theorem (Zhang, 2005):

$$P\left(c \mid X\right) = \frac{P\left(X \mid c\right) P\left(c\right)}{P\left(X\right)}$$

$P\left(c \mid X\right)$: The Prior probability of class

$P\left(X \mid c\right)$: The Posterior probability

$P\left(c\right)$: The Likelihood

$P\left(X\right)$: The Predictor Prior probability

$$P\left(c \mid x\right) = \prod_{i=1}^{n} P\left(x_i \mid c\right)$$

Demarche:

Phase One: Calculate Posterior probability for each class**:**

Good / excellent / poor / bad / …

$$P(c \mid x) = \frac{P\left(x \mid c\right) P\left(c\right)}{P\left(x\right)}$$

$$P\left(c \mid x\right) = \prod_{i=1}^{n} P\left(x_i \mid c\right) = P\left(x_1 \mid c\right) \times P\left(x_2 \mid c\right) \times P\left(x_3 \mid c\right) \ldots P\left(x_n \mid c\right) \times P\left(c\right)$$

Phase Two: Calculate sum:

Sum = $\sum_{1}^{n} P_i = P_1 + P_2 + P_3 + \ldots + P_n$ / i: is the instance index.

Phase Three: Calculate percentage for each instance:

$$Percentage\left(i\right) = \frac{P_i}{Sum}$$

Considering this sample of dataset taken from a real world dataset (used in case study) with just four attributes (Table 1).

The posterior probability can be calculated after, constructing a frequency table for each attribute and transforming the frequency tables to likelihood tables (Figure 2).

Assuming that we have three fields (Table 2).

Demarche:

Phase One: Calculate probability for class "Accepted":

$$P(c \mid x) = P\left(x_1 \mid c\right) \times P(x_2 \mid c) \times P\left(x_3 \mid c\right) \ldots P\left(x_n \mid c\right) \times P\left(c\right)$$

P1(Accepted)=(6/11)x(2/11)x(7/11)x(2/11)x(11/20)=0.0063
P2 (Accepted) = 0.0289
P3 (Accepted) = 0.0631

Phase Two: Calculate sum:

Sum = $\sum_{1}^{n} P_i$ / i: is the instance index

Sum = 0.0983

Phase Three: Calculate percentage for each instance:

$$Percentage\left(i\right) = \frac{P_i}{Sum}$$

Percentage (1) = 0.0063 / 0.0983= 0.064 → 6.4%
Percentage (2) = 0.0289 / 0.0983= 0.2939 → 29.4%
Percentage (3) = 0.0631/ 0.0983= 0.6419 → 64.2%
6.4% + 29.4% +64.2% = 100% = 1

The results will help the planning staff to make the suitable decision or choice between alternatives. Their decision may not be the one that achieve the highest percentage; thus, the system will consider this action, and surely will change its behavior next time even the same inputs.

Clustering Process

The second internal process is the clustering; this addresses how to obtain good impressions of citizens by predicting the diverse desire and tendencies after detecting the different categories basing on historical data.

In the previous section, we described how we use naïve Bayes classifier. As shown above, it is used for classification. We have previously defined number of classes (good / excellent / poor) and we want to classify the new instances. The problem if we do not know what the classes are. Moreover, how many classes do we have, the solution is the clustering (also called unsupervised learning).

We propose to manage the database of citizens as well as the historical data. In the database, we have the public participation as shown in the architecture (figure 1), which means that we have the vote of each citizen, for the projects, in which he has participated, and who was informed by different ways mobile messages and e-Mail. Our idea here is to categorize the citizens, depending on their participation, active citizens (their participation varies: satisfied, dissatisfied, indifferent…), passive citizens (always dissatisfied) …and after that we get the passive ones, that attended over the threshold of votes.

Basing on Johnson algorithm, (D'Andrade, 1978), which is an agglomerative clustering we classify citizens in different categories (clusters). As we have binary data, which varies between satisfied, dissatisfied or indifferent. In addition, the attributes (projects) that we have are asymmetric. The first step is building the contingency table (also called dissimilarity table), it is based on four dependent quantities: a, b, c and d (Warrens, 2008), as shown in Table 3 in the appendix.

In similarity measure different distances are used depends on data type. For binary data, Jaccard coefficient is used.

Jaccard coefficient: $D_{Jac} = \dfrac{b+c}{a+b+c}$

Considering that: V the group of clusters where: V= {C1, C2, C3... Cn}.

Johnson's algorithm in single linkage method in five steps:

Begin

Step 1: Each item (citizen in our case) represent a cluster, in other words N items signify N clusters.

Step 2: Calculate similarity between clusters using Jaccard coefficient.

Step 3: Fuse the most similar pair of cluster into one cluster, which means we have now N-1 clusters.

Step 4: Update the similarities values between the new cluster and each of the old clusters by take the smallest value:

New Distance = $\min(D_{Jac}$ (Ci, V-{Ci}), $D_{Jac}\left(Cj, V-\left\{Cj\right\}\right))$ /i, j index of the merged pair clusters.

Step 5: Repeat steps 3 and 4 until we have the number of cluster we want.

End.

Considering this sample of dataset of citizens (Table 4) taken also from real dataset (of the case study), which contains 6 citizens which voted for five projects (Y mean Yes or satisfied, N mean No or not satisfied).

Calculate the distances is the first step of our process after the contingency table (table 5):

$$D\left(Citizen_1, Citizen_2\right) = \frac{b+c}{a+b+c} = \frac{0+1}{4+0+1} = \frac{1}{5} = 0.2$$

The distance between Citezen_1 and Citizen_2 is 0.2.
Same procedure for each pair of citizens:

$$D\left(Citizen_1, Citizen_3\right) = \frac{2+1}{2+2+1} = \frac{3}{5} = 0.6$$

$$D\left(Citizen_1, Citizen_4\right) = \frac{2+0}{2+2+0} = \frac{2}{4} = 0.5$$

$$D\left(Citizen_3, Citizen_4\right) = \frac{2+1}{1+2+1} = \frac{3}{4} = 0.75$$

$$D\left(Citizen_5, Citizen_6\right) = 0$$

Basing on the distance table (Table 6) we apply Johnson's algorithm, the results are shown in Figure 3 (history of clusters) in the appendix.

Collecting Data Process

The other process collecting data is the procedure in which we collect (get it if exist) a history of the strategies, whether good, bad or poor, which were previously selected as alternatives for projects and those who are proposed by the urban planning staff. This process covers the collection and organization of data from different sources such as Comma Separated Value (csv) files, text files (txt) and other formats from which we can extarct the data.

User Interface Module

The IDSS is provided with a user interface, which is designed to be ergonomic and simple for the user, allowing amenities in all the planning phases in order to decrease the effort.

The proposed architecture of IDSS is designed to assist decision makers (DMs) in the planning process. It assumes that a set of strategies (alternatives) has been identified and generated, and that the trick is to provide decision support in the selection of the finest alternatives, according to previous strategies consequences. Although the IDSS was designed to treat a particular issue (prediction of strategies consequences), and since the internal processes (naïve Bayes and clustering) could be used individually, as well as together, it could also be applicable to other issues and decision problems in other domains.

CASE STUDY

In our case study, we chose the field choice problem, which is a multi-sectoral problem that comprises dozen of administrations in various departments (agriculture, town planning, public works, building and housing, etc.). In front of the decision problem (Section 2), our system will foretell for each proposed field whether accepted or refused, and make rankings of them according to the percentage of the class accepted. We developed a prototype of an IDSS for urban planning that assist decision makers in several phases (Figure 5) of urban planning process. We sheds light on hosting site choice phase, using java programming in eclipse, and the following tools (Figure 4):

1. Ubuntu 14.04 Long Term Support (LTS) open source operating system (Trusty Tahr) which use The Linux kernel 3.13, available on the officiel website of Ubuntu.
2. MySQL 5.7 open source Relational Data Base Management System (RDBMS), which represents one of the best release of the this popular open source database that provides a new, advanced feature sets such as Geographical Information System (GIS) Spatial Extensions, multi-source replication and many other enhancements, also HBase, the second type of database that we used. It represents a non-relational, scalable and distributed database that supports structured data storage for large tables, and that use Hadoop Distributed File System (HDFS) to store the data (White, 2012).
3. Eclipse IDE for java EE developers is the tool that we used in the development of this study case. It is an integrated development environment (IDE) used in computer programming issues and it is predominantly used for developing Java applications.

Other tool that we have used is Weka. It is a collection of machine learning algorithms for data mining issues. The algorithms can either be applied directly to a dataset or called from Java codes, and modified to assume specific aims; also, it is possible to apply it on big data. We integrated Weka plugin in eclipse to use the machine learning algorithms that exist in it (naïve Bayes, k-means, decision trees, and many others).Weka is an open software source (Hall et al., 2009).

The IDSS can increase the knowledge of planning actors on their territory, provide reliable measurements, improve vertical cooperation between the different administrative echelons and ultimately produce policies. Our system provides also relevant assistance to public authorities during all the phases of planning process from the requirement census to project realization (figure 5).

In order to show the autonomy of the system in changing behavior even through same inputs, a real life scenario is presented below.

The Fields (Figure 6) number 4,6,7 and 10 have been predicted to be accepted with the highest percentage (10.91%), we choose another field (field number 5) which has 10.69%, and validate it to see how the system react with same data. Same Previous inputs are entered again and classified, in the picture the results.

The highest percentage (Figure 7) is given to the filed 5 (13.75), also in charts (Figure 8), so the system change the results although the same data is entered. The experiments that were carried out show how the prototype changes its behavior autonomously from use to another. The information of the case study's dataset and alternatives are summarized in table 7 in the appendix.

CONCLUSION

The clear sign of the decision complexity in urban planning is the existence of multiple criteria and several entities in the decision making process. Besides several decision factors: politics, socioeconomic, cultural and other factors, where in each project's realization, there are different consequences that can be excellent, good, poor or bad. We proposed an intelligent decision support system that has the ability to anticipate future evolutions, to afford pertinent assistance and cooperation, besides offering better assistance.

Thus, we have initiated within the domain of intelligent decision support a new methodology, combining data mining techniques and machine learning algorithms.

First, Naïve Bayes is used to make prediction of the strategy consequences whether accepted or denied and to classify the alternatives.

Second, Agglomerative clustering categorizes the participants of citizens in process into several groups: passive, active, and indifferent. The categorization aims to bring public authorities closer to citizens.

Third, we used both relational data base management system (RDBMS) as well as Big data tools, to manage the huge amounts of data, which cannot be managed with RDBMS, but the user still has the choice.

From the research that has been undertaken, it is possible to conclude that the results of the proposed system's methodology has been very successful and quite convincing for the majority of the cited problems, nevertheless, there are still some exciting and germane issues to be addressed.

For future work, it would be interesting to go further in this domain by integrating other techniques and technologies, like cloud computing and Internet Of Things (IOT) in order to improve the functionalities of this system to a greater extent. We also believe that we could contribute in the domain of smart cities.

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REFERENCES

Aronson, J. E., Liang, T. P., & Turban, E. (2005). *Decision support systems and intelligent systems*. Pearson Prentice-Hall.

Asadi, R., & Ghatee, M. (2015). A rule-based decision support system in intelligent Hazmat transportation system. *IEEE Transactions on Intelligent Transportation Systems*, *16*(5), 2756–2764. doi:10.1109/TITS.2015.2420993

Benatia, I., Laouar, M. R., Bendjenna, H., & Eom, S. B. (2016). Implementing a cloud-based decision support system in a private cloud: The infrastructure and the deployment process. *International Journal of Decision Support System Technology*, *8*(1), 25–42. doi:10.4018/IJDSST.2016010102

Benatia, I., Laouar, M. R., Eom, S. B., & Bendjenna, H. (2016). Incorporating the Negotiation Process in Urban Planning DSS. *International Journal of Information Systems in the Service Sector*, *8*(2), 14–29. doi:10.4018/IJISSS.2016040102

Benatia, I., Ridda Laouar, M., Bendjenna, H., & Eom, S. B. (2015). A cloud-based multi-criteria decision support system for selecting urban housing projects. *Human Systems Management*, *34*(2), 119–132. doi:10.3233/HSM-140826

Chakhar, S., & Mousseau, V. (2009). Generation of spatial decision alternatives based on a planar subdivision of the study area. In *Advanced Internet Based Systems and Applications* (pp. 137–148). Springer. doi:10.1007/978-3-642-01350-8_13

Chen, G., Wang, E., Sun, X., & Tang, Y. (2015). An intelligent analysis and mining system for urban lighting information. *International Journal of Smart Home*, *9*(3), 253–262. doi:10.14257/ijsh.2015.9.3.23

Chichernea, V. (2014). The use of Decision Support Systems (DSS) in Smart City planning and management. Journal of Information Systems & Operations Management, 1.

Coutinho-Rodrigues, J., Simão, A., & Antunes, C. H. (2011). A GIS-based multicriteria spatial decision support system for planning urban infrastructures. *Decision Support Systems*, *51*(3), 720–726. doi:10.1016/j.dss.2011.02.010

D'Andrade, R. G. (1978). U-statistic hierarchical clustering. *Psychometrika*, *43*(1), 59–67. doi:10.1007/BF02294089

Ghavami, S. M., Taleai, M., & Arentze, T. (2017). An intelligent spatial land use planning support system using socially rational agents. *International Journal of Geographical Information Science*, *31*(5), 1022–1041. doi:10.1080/13658816.2016.1263306

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: An update. *SIGKDD Explorations*, *11*(1), 10–18. doi:10.1145/1656274.1656278

Iscaro, G., & Nakamiti, G. (2013, February). A supervisor agent for urban traffic monitoring. In *Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), 2013 IEEE International Multi-Disciplinary Conference on* (pp. 167-170). IEEE. doi:10.1109/CogSIMA.2013.6523842

Iskin, I., Daim, T. U., Noble, S., & Baltz, A. (2014). Approaching IT automation decisions using analytic hierarchy process (AHP). *International Journal of Information Technology Project Management*, *5*(1), 77–89. doi:10.4018/ijitpm.2014010107

Johnson, S. C. (1967). Hierarchical clustering schemes. *Psychometrika*, *32*(3), 241–254. doi:10.1007/BF02289588 PMID:5234703

Kaklauskas, A. (2015). Intelligent decision support systems. In *Biometric and Intelligent Decision Making Support* (pp. 31–85). Springer International Publishing.

Kar, A. K. (2015). A hybrid group decision support system for supplier selection using analytic hierarchy process, fuzzy set theory and neural network. *Journal of Computational Science*, *6*, 23–33. doi:10.1016/j.jocs.2014.11.002

Khediri, A., & Laouar, M. R. (2018a). Deep-Belief Network Based Prediction Model for Power Outage in Smart Grid. In *Proceedings of the 4th ACM International Conference of Computing for Engineering and Sciences* (p. 4). ACM. doi:10.1145/3213187.3287611

Khediri, A., & Laouar, M. R. (2018b). Intelligent Decision Support System for Electric Power Restoration. In *Proceedings of the 7th International Conference on Software Engineering and New Technologies* (p. 17). ACM. doi:10.1145/3330089.3330117

Khediri, A., Laouar, M. R., & Eom, S. B. (2019). Decision Support System Architecture for Smart Grid's Hardening Against Weather Hazard. In *International Conference on Advanced Intelligent Systems for Sustainable Development* (pp. 77-89). Springer.

Knox, P. L., Marston, S. A., & Imort, M. (2016). *Human geography: Places and regions in global context*. Pearson.

Konidari, P., & Mavrakis, D. (2007). A multi-criteria evaluation method for climate change mitigation policy instruments. *Energy Policy*, *35*(12), 6235–6257. doi:10.1016/j.enpol.2007.07.007

Laouar, M. R. (2005). *Contribution pour l'aide à l'évaluation de projets de déplacements urbains* (Doctoral dissertation). Valenciennes.

Laslo, Z., & Gurevich, G. (2000). A simulation-based decision support system for managing information technology project portfolios. *International Journal of Information Technology Project Management*, *4*(2), 1–17. doi:10.4018/jitpm.2013040101

Laurini, R. (2001). *Information systems for urban planning: A hypermedia co-operative approach*. Taylor & Francis.

Massam, B. H. (1988). Multi-criteria decision making (MCDM) techniques in planning. *Progress in Planning*, *30*, 1–84. doi:10.1016/0305-9006(88)90012-8

Moghadam, S. T., Delmastro, C., Lombardi, P., & Corgnati, S. P. (2016). Towards a New Integrated Spatial Decision Support System in Urban Context. *Procedia: Social and Behavioral Sciences*, *223*, 974–981. doi:10.1016/j.sbspro.2016.05.334

Ofli, F., Meier, P., Imran, M., Castillo, C., Tuia, D., Rey, N., Briant, J., Millet, P., Reinhard, F., Parkan, M., & Joost, S. (2016). Combining human computing and machine learning to make sense of big (aerial) data for disaster response. *Big Data*, *4*(1), 47–59. doi:10.1089/big.2014.0064 PMID:27441584

Park, M. H., & Stenstrom, M. K. (2008). Classifying environmentally significant urban land uses with satellite imagery. *Journal of Environmental Management*, *86*(1), 181–192. doi:10.1016/j.jenvman.2006.12.010 PMID:17291679

Power, D. J. (2002). Decision Support Systems: Concepts and Resources for Managers. *Studies in Informatics and Control*, *11*(4), 349–350.

Rienow, A., & Goetzke, R. (2015). Supporting SLEUTH–Enhancing a cellular automaton with support vector machines for urban growth modeling. *Computers, Environment and Urban Systems*, *49*, 66–81. doi:10.1016/j.compenvurbsys.2014.05.001

Rikalovic, A., Cosic, I., Labati, R. D., & Piuri, V. (2017). Intelligent Decision Support System for Industrial Site Classification: A GIS-Based Hierarchical Neuro-Fuzzy Approach. *IEEE Systems Journal*.

Roy, B. (1990). The outranking approach and the foundations of ELECTRE methods. In *Readings in multiple criteria decision aid* (pp. 155–183). Springer. doi:10.1007/978-3-642-75935-2_8

Roy, B. (2005). Paradigms and Challenges, Multiple Criteria Decision Analysis-State of the Art Survey. *Multicriteria International Series in Operations Research & Management Science*, *78*, 3–24. doi:10.1007/0-387-23081-5_1

Simon, H. A. (1960). The Ford distinguished lectures: Vol. 3. The new science of management decision. Academic Press.

Velasquez, M., & Hester, P. T. (2013). An analysis of multi-criteria decision making methods. *International Journal of Operations Research*, *10*(2), 56–66.

Warrens, M. J. (2008). *Similarity coefficients for binary data: properties of coefficients, coefficient matrices, multi-way metrics and multivariate coefficients. Psychometrics and Research Methodology Group*, Leiden University Institute for Psychological Research, Faculty of Social Sciences, Leiden University.

White, T. (2012). *Hadoop: The definitive guide*. O'Reilly Media, Inc.

Yang, Y., Tan, W., Li, T., & Ruan, D. (2012). Consensus clustering based on constrained self-organizing map and improved Cop-Kmeans ensemble in intelligent decision support systems. *Knowledge-Based Systems*, *32*, 101–115. doi:10.1016/j.knosys.2011.08.011

Zhang, H. (2005). Exploring conditions for the optimality of naive Bayes. *International Journal of Pattern Recognition and Artificial Intelligence*, *19*(02), 183–198. doi:10.1142/S0218001405003983

Zhou, H., Noble, C., & Cotter, J. (2015, December). A big data based intelligent decision support system for sustainable regional development. In *Smart City/SocialCom/SustainCom (SmartCity), 2015 IEEE International Conference on* (pp. 822-826). IEEE. doi:10.1109/SmartCity.2015.169

APPENDIX

Table 1. Sample of the fields' dataset

Terrain nature	Existing pole	Juridical nature	Underground cables	Decision
Agricultural	High voltage	Private	Non-existent	Refused
Agricultural	High voltage	Private	Exist	Refused
Buildable	High voltage	Private	Non-existent	Accepted
Clayey	Medium voltage	Private	Non-existent	Accepted
Clayey	Low voltage	State-owned	Non-existent	Accepted
Clayey	Low voltage	State-owned	Exist	Refused
Buildable	Low voltage	State-owned	Exist	Accepted
Agricultural	Medium voltage	Private	Non-existent	Accepted
Agricultural	Low voltage	State-owned	Non-existent	Accepted
Clayey	Medium voltage	State-owned	Non-existent	Refused
Agricultural	Medium voltage	State-owned	Exist	Accepted
Buildable	Medium voltage	Private	Exist	Accepted
Buildable	High voltage	State-owned	Non-existent	Accepted
Clayey	Medium voltage	Private	Exist	Refused
Buildable	Low voltage	Private	Non-existent	Accepted
Buildable	Low voltage	State-owned	Exist	Refused

Table 2. Characteristics of the new fields

Terrain Nature	Existing pole	Juridical nature	Underground cables
Buildable	High voltage	State-owned	Exist
Buildable	Low voltage	Private	Non-existent
Buildable	Medium voltage	State-owned	Non-existent

Table 3. Contingency table

1^{st}Variable	2^{nd} Variable		Total
	Value 1	Value 0	
Value 1	A	B	p_1
Value 0	C	D	q_1
Total	p_2	q_2	Sum $p_1\ p_2\ q_1\ q_2$

Table 4. Citizens' Dataset

	Project1	Project2	Project3	Project4	Project5
Citizen1	Y	Y	Y	Y	N
Citizen2	Y	Y	Y	Y	Y
Citizen3	N	N	Y	Y	Y
Citizen4	N	Y	Y	N	N
Citizen5	N	N	N	N	N
Citizen6	N	N	N	N	N

Table 5. Contingency table (Citizen_1 and Citizen_2)

		Citizen_2		
		1	0	Sum
Citizen_1	1	4	0	4
	0	1	0	1
	Sum	5	0	5

Table 6. Distance table

Citizen	C1	C2	C3	C4	C5	C6
C1	0	0.2	0.6	0.5	1	1
C2		0	0.4	0.6	1	1
C3			0	0.75	1	1
C4				0	1	1
C5					0	0
C6						0

Table 7. Summarize of the experiment

Input criteria	Output	Dataset	Alternatives
15 criteria per field: nature of land, underground installations, Existing pole, Juridical nature…	Classes: accepted, refused. Ranking of fields	120 field as models used for learning	10 fields to predict and choose

Figure 1. The proposed architecture for the IDSS

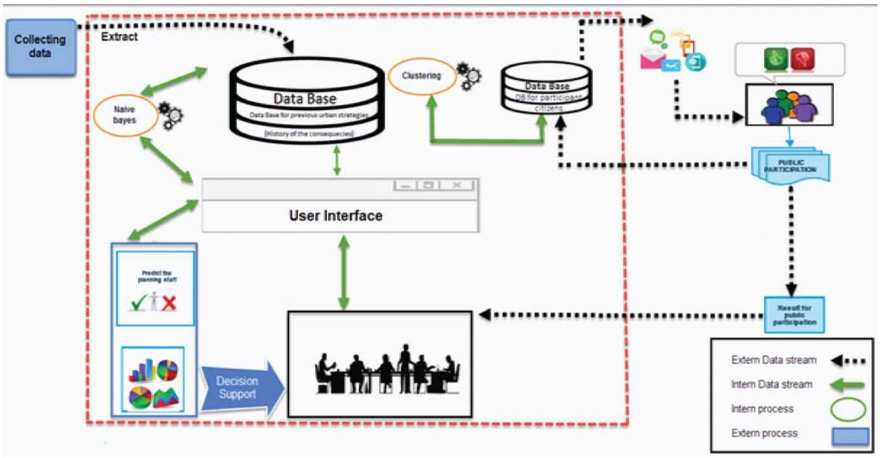


Figure 2. Calculate posterior probability for a single attribute

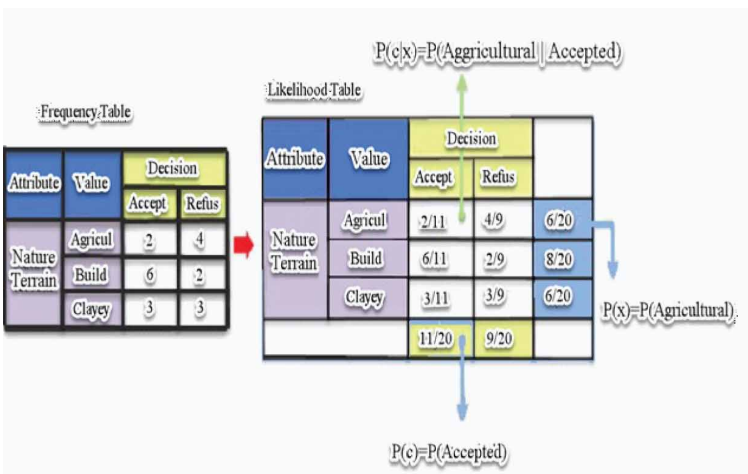


Figure 3. Generated dendrogram

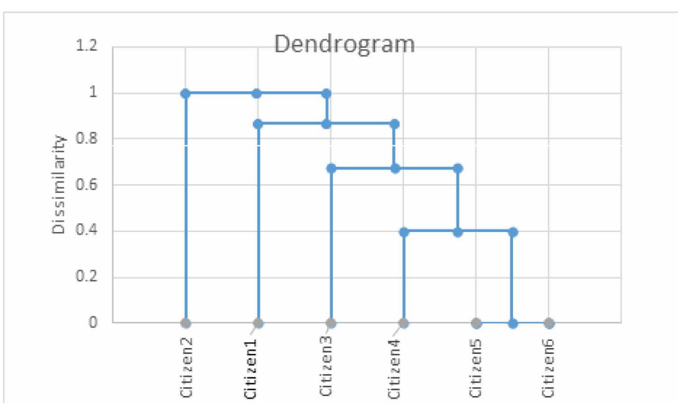


Figure 4. Case study IDSS tools

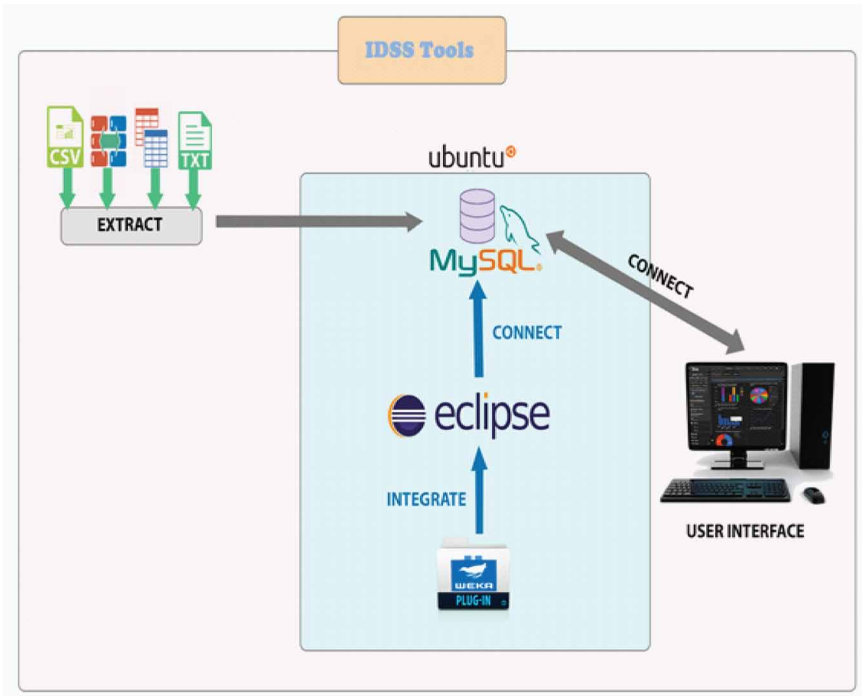


Figure 5. IDSS's provided assistance in urban

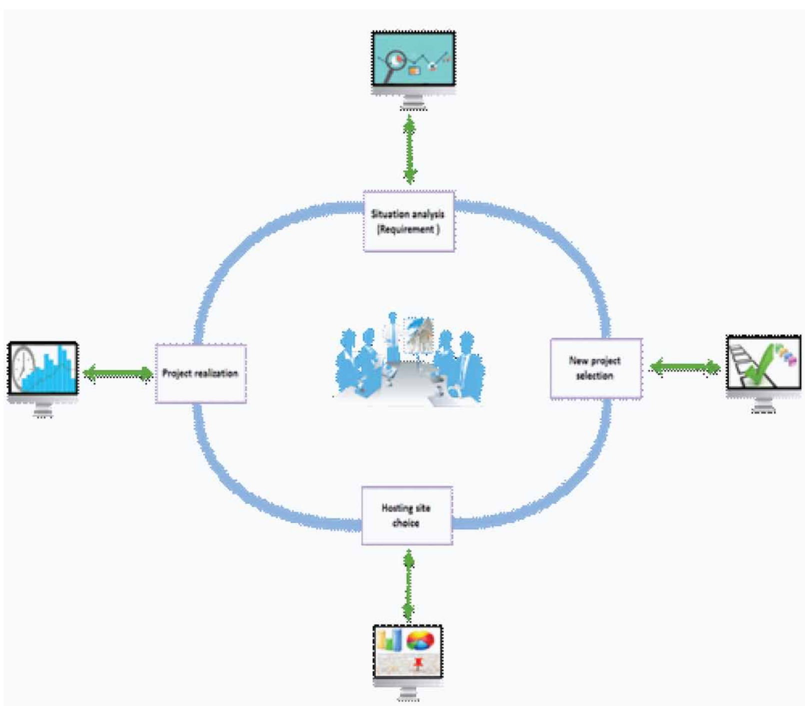


Figure 6. First result before choice

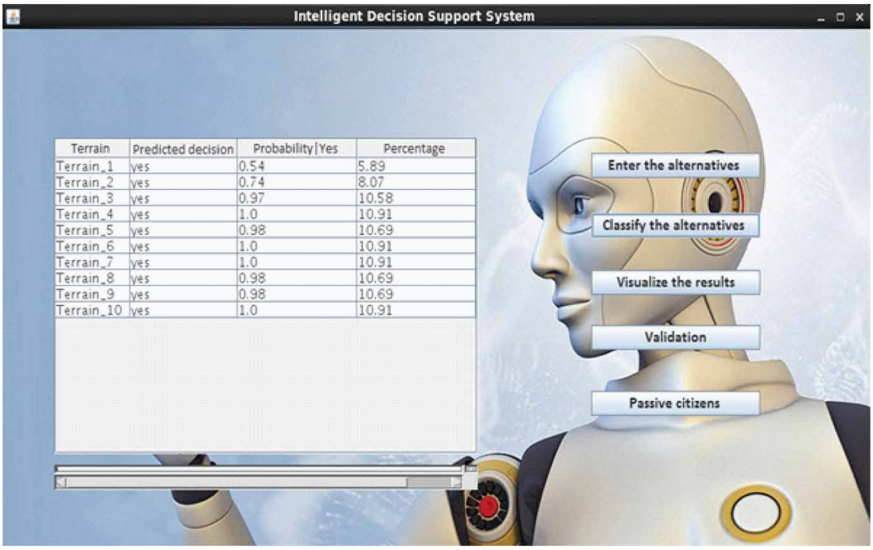


Figure 7. Results after choice

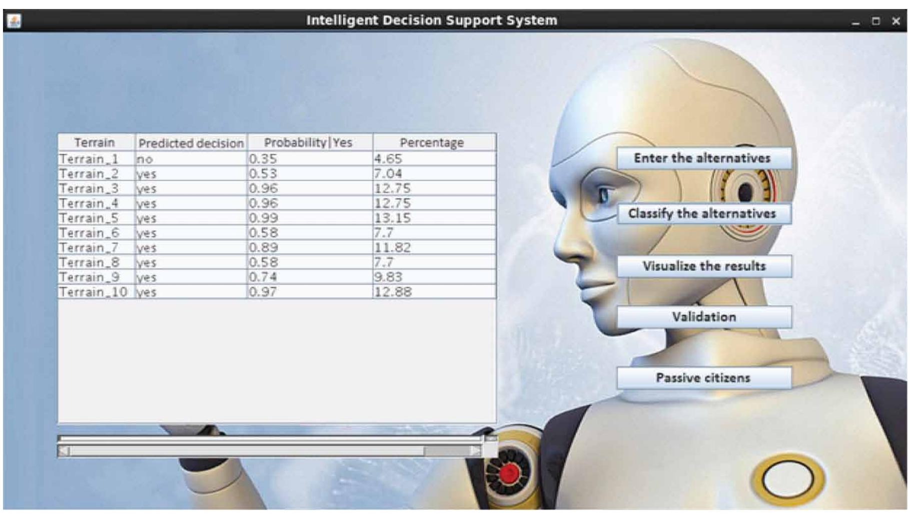
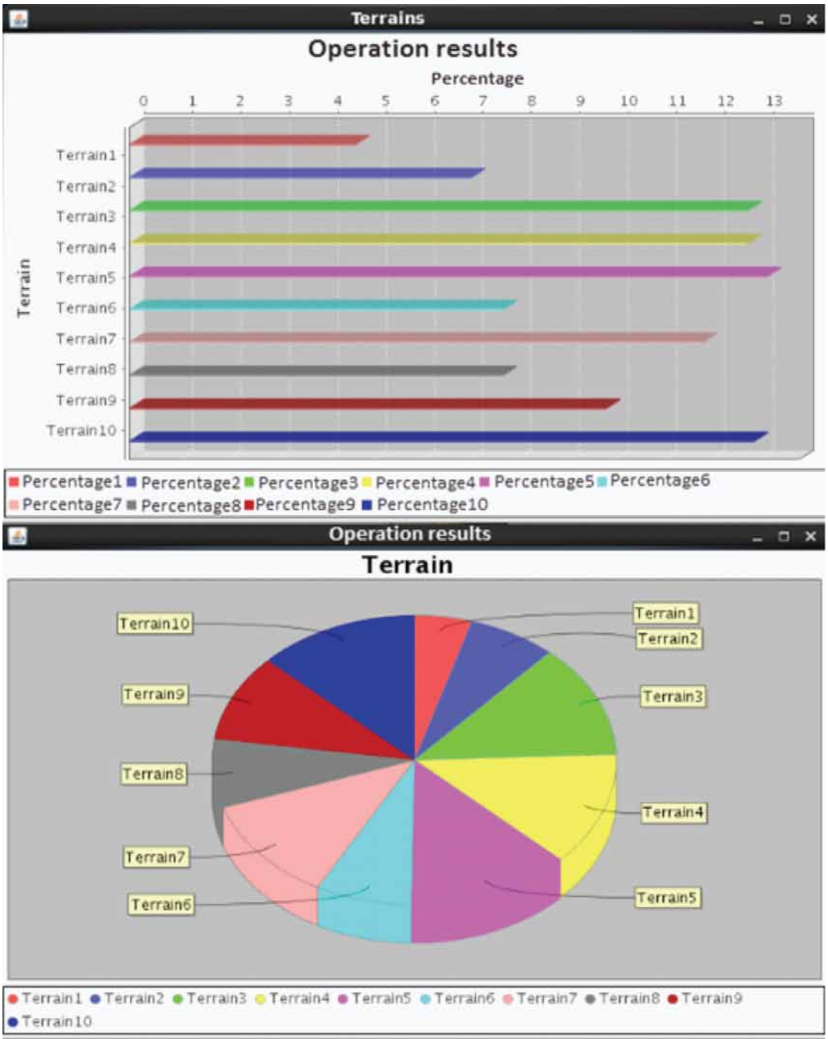


Figure 8. Charts after choice



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