Implementation of Chaid Algorithm: A Hotel Case

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Abstract

Today, companies are planning their own activities depending on efficiency and effectiveness. In order to have plans for the future activities they need historical data coming from outside and inside of the companies. However, this data is in huge amounts to understand easily. Since, this huge amount of data creates complexity in business for many industries like hospitality industry, reliable, accurate and fast access to this data is to be one of the greatest problems. Besides, management of this data is another big problem. In order to analyze this huge amount of data, Data Mining (DM) tools, can be used effectively. In this study, after giving brief definition about fundamentals of data mining, Chi Squared Automatic Interaction Detection (CHAID) algorithm, one of the mostly used DM tool, will be introduced. By CHAID algorithm, the most used materials in room cleaning process and the relations of these materials based on in a five star hotel data are tried to be determined. At the end of the analysis, it is seen that while some variables have strong relation with the number of rooms cleaned in the hotel, the others have no or weak relation.

Keywords: Data Mining; CHAID; Tourism; Hotel

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1. Introduction

Most of the companies try to establish their own databases for prediction and further analysis. Data mining is the collection of techniques which are discovered the hidden pattern of data from huge big datasets stored in databases. Data mining is the process of understanding, preparing, modelling, and analyzing data. It is the way of extracting potentially useful information and knowledge and uncovering unknown patterns and relationships hidden in datasets (Rupnik, Kukar, Bajec, & Krisper, 2006; Ha & Park, 1998; Clifton & Thuraisingham, 2001; Shaw, Subramaniam, Tan, & Welge, 2001; Huang, Wu, & Chou, 2013; Cheng & Chen, 2009; Gargano & Raggad, 1999; Windle, 2004; Han, Kamber, & Pei, 2012: 2).

Data mining differs from conventional statistical techniques at its capability in artificial intelligence and use several techniques and technologies together like; statistical, machine learning techniques, structured query language (SQL), decision trees, neural networks, rule induction and graphic visualization, fuzzy logic and genetic algorithms (Shaw et al., 2001; Gargano & Raggad, 1999; Han et al., 2012: 23). In other words, it is a multidisciplinary area that intersects with statistics, machine learning, and database management (Feelders, Daniels, & Holsheimer, 2000). This process is called Cross Industry Standard Process for Data Mining (CRISP-DM) which has 6 steps: business understanding, data understanding, data preparation, modelling (DM), evaluation, deployment (Shearer, 2000). The first step is to try to understand the needs of establishment, kind of problem you are faced with. The second step includes collection of sample data and which data will needed, including its format and size. The data preparation step involves sampling of data, running correlation and significance tests, cleaning data like checking for completeness of data records and correction for noise. Modelling step involves usage of the planned data mining tools. Evaluation step includes understanding the results by owners of the data who check whether the new information is truly novel and interesting and checking the impact of the discovered knowledge. The deployment step consists of planning where and how the discovered knowledge will be used (Cios & Kurgan, 2005).

Chi Squared Automatic Interaction Detection (CHAID) is one of the most useful data mining tool to catch such a pattern in data warehouses. It can be used as a classification or regression trees (Oztekin, 2011). Since it has branches and bounds, structure of it looks like a decision tree.

This paper tries to determine the most used materials in room cleaning process and the relations of them in a five star hotel by CHAID algorithm.

2. Literature Review

Material planning and purchase decisions in hotels have been done regularly depends on type of hotel and location. In order to decrease the operational costs efficient planning tools and methods must be used (Jannadi & Al-Isa, 1995; Kappa, Nitchke, & Schappert, 1995: 113). For efficient planning, the mostly used materials and their usage must be analyzed.

There are lots of studies about hotel housekeeping process such as; basic functions of process (Medlik & Ingram, 2000; Powell & Watson 2006; Weaver 1993; Saleh & Ryan 1992; Jones 2005; Becker 2001; Jannadi & Al-Isa 1995; Boon 2007; Grady 2005; George & Hançer 2008), personnel profile (Şafak, 2006; Powell & Watson, 2006; Woods & Viehland, 2000), motivation (Faulkner & Patiar, 1997; Peterson, 2011; Yap, 2011; Hsu, Ho, Tsai, & Wang, 2011; Madanoğlu, Moreo, & Leong, 2003; Digiulio, 2010; Selwitz, 2001), outsourcing & quality (Lamminmaki, 2009; Tochner, 2011; Burt, 2010; Wan & Su, 2010; Jones & Siag, 2009). However there is no study using DM tools which are related with material planning for housekeeping processes.

In literature review, it is seen that there are lots of studies used CHAID algorithm which are first started with Kass (1980). Antipov & Pokryshevskaya, 2010 who used CHAID based approach to detect classification accuracy

heterogeneity across segments of observations. They used churn data of UCI Repository of Machine Learning Database.

Rygielski Wang, & Yen, 2002 try to examine pros and cons of CHAID and neural network with in a case studies for one of retailer and one home equity marketer. They conclude CHAID has better performance than neural nets.

Jurado & Leon, 2013 use CHAID to identify patient behavior for diagnosis and treatment. McCarty & Hastak, 2007 try to test performance of RFM, CHAID and logistic regression methods for direct marketing in two different data sets. They find that CHAID has a better performance than RFM in relatively small database, while RFM is better for other cases.

Kleppin, Pesch, & Schröder, 2008 try to examine the factor affecting metal concentrations in the mosses. They use CHAID to make classification. Unguren & Doğan, 2010 try to determine the personnel job satisfaction in a five star hotel in Turkey. They use CHAID analysis for clustering and find that single young managers are more motivated than others.

Karathiya, Sakshi, & Sakshi, 2012 try to organize a rule based tour plan with data taken from his survey held on Gujarat destination in India. And also he prepare a target mailing list according the response to his survey. As a result he categorize the most popular attractions in this region.

As a result, it is seen that there is no study using DM tools for material planning for housekeeping process.

3. Research and Methodology

In this study, the relation of the independent variable which is the number of rooms to be cleaned with the dependent variables which are 8 chemicals used in the cleaning process is examined by CHAID algorithm which is one of the DM tools. The basic purpose of this study is to determine the importance of each of these 8 chemicals in the cleaning process. Besides, it is thought that some of these chemicals are much more important, so the most important chemical(s) is try to be determined. For the analysis of data, IBM SPSS Modeler 15.0 software package is used.

For the implementation of this method, a five star hotel is chosen. After one month observation, the acquired data is enlarged by the method of bootstrapping. Bootstrapping method is a method that is frequently used for the insufficient data. Efron (1979) introduced the Bootstrap method firstly. The idea behind bootstrap is to use the data of a sample study at hand as a “surrogate population”, for the purpose of approximating the sampling distribution of a statistic; i.e. to resample (with replacement) from the sample data at hand and create a large number of “phantom samples” known as bootstrap samples (Singh & Mie, 2014).

The bootstrap refers to the use of the original data set to generate new data sets (Efron & Tibshirani, 2009). For certain "known" populations and well-behaved parameters, we know quite a bit about the properties of the sample estimates, and can be confident in these results. Bootstrapping seeks to uncover more information about the properties of estimators for "unknown" populations and ill-behaved parameters (IBM SPSS, bootstrapping notes).

The used data in this study is bootstrapped from the original data by this method. In another way, it is said that the method generates a phantom sample for the study. Therefore, the study can be handled by this bootstrapped data which is close to the real population.

In this study, a decision tree is created by CHAID algorithm (Appendix 1). CHAID is a type of decision tree technique, based upon adjusted significance testing (Bonferroni testing) generally used by categorical variables (Antipov & Pokryshevsk, 2010; Chien, Wang, & Cheng, 2007; Van Diepen & Franses, 2006). CHAID is one of the oldest tree classification methods originally proposed by Kass (1980). CHAID "build" non-binary trees (i.e., trees where more than two branches can attach to a single root or node) and the algorithm yields many multi way frequency tables (Antipov & Pokryshevsk, 2010).

CHAID proceeds in steps, first the best partition for each predictor is found. Then the predictors are compared and the best one is chosen. The data are subdivided according to this chosen predictor. Each of these subgroups are re-analyzed independently, to produce further subdivision for analysis (Kass, 1980). For each selected pair, CHAID checks if the p-value obtained is greater than a certain merge threshold. If the answer is correct, it merges the values and searches for an additional potential pair to be merged. The process is repeated until no significant pairs are found (Maimon & Rokach, 2010: 164; Sanchez & Borja, 2008).

CHAID can be used to solve prediction problems (Rygielski, et al., 2002). Classification and regression trees are also known as recursive partitioning, segmentation trees or decision trees and are widely used either as prediction or exploratory tools (Murph & Comiskey, 2013). The mostly used regression trees are CART and CHAID in the literature (Öztekin, 2011).

4. Results and Findings

After the implementation of CHAID method in five star hotel and analysis of bootstrapped data, it is seen that the decision tree has five depth and the first branching is in the dependent variable X_6 , which is the room cleaner. This shows us that the most used chemical among 8 chemicals is X_6 , room cleaner. These findings can also be seen in Figure 1 and Appendix 1 ($F=488.910$, $p < 0.05$).

When Figure 1 is examined, after X_6 , the most next used chemical is X_1 and the others according to their importance are respectively X_8 , X_4 , X_7 , X_2 and X_5 . Since CHAID algorithm shows the relation of the independent variable to the dependent variables, in this analysis it is easily said that the dependent variable X_6 has a strong relation with the independent variable (Y , number of rooms to be cleaned) relative to the other dependent variables (Figure 1, $X_6 > 0.4$, $X_1, X_8, X_4, X_7, X_2, X_5 < 0.2$).

Figure 1: Mostly Used Material and Their Usage Ratio

Since we have continuous variables in this study, we used F-table values. The p and F values of the bootstrapped data are summarized in Table 1 for the decision tree. When Table 1 is examined, all the p- values are under 0.05, ($p \leq 0.05$) so it shows us that all nodes in each branching generates correct solutions. Moreover, there is a relation between X_6 and independent variable Y (target variable). In the first branching there are 9 nodes and within these 9 nodes the fifth node generates the closest solution. After the first branching, there is also another branching for the independent variables excluding X_2 and X_3 . Besides, it shows us that the value of X_6 can be forecasted by the analysis of other variables, X_1 , X_4 , X_5 , X_7 and X_8 . So, independent variables X_1 , X_4 , X_5 , X_7 and X_8 can be used as a predictor for X_6 and independent variable, Y.

Table 1. Statistics for First Branch

# of Branch	Interval	p-Values*		F-Table
0	-	0.000	0	488.91
1	$X_6 \leq 176.400$	0.004		
2	$X_6 > 176.400$ and $X_6 \leq 219.600$	0.001		22.909
3	$X_6 > 219.600$ and $X_6 \leq 259.200$	0.007		22.898
4	$X_6 > 259.200$ and $X_6 \leq 300$	0.001		12.893
5	$X_6 > 300$ and $X_6 \leq 331.200$	0.001		31.335
6	$X_6 > 331.200$ and $X_6 \leq 374$	0.020		30.005
7	$X_6 > 374.400$ and $X_6 \leq 446.400$	0.000		12.126
				45.186

* <0.05

In the second branching, node 10 generates the closest result for X_6 and X_4 can be used as a predictor of X_6 if $X_4 \leq 12.6$ for the target variable ($X_6 = 42.667$). It means that the value of X_4 leads us to find solution for the dependent variable X_6 and as one example, the amount of X_6 to be purchased can be determined from the value of X_4 . The other node which is 13 indicates that dependent variable X_6 can be forecasted according to value of dependent variable X_8 if $133.4 < X_8 < 180$ based on the relations between dependent variables X_6 and X_8 ($X_6 = 56.800$).

Moreover, in the second branching it is seen that node 15 (for $X_1 \leq 48.3$) and node 16 (for $X_1 > 48.3$) has the same result. Either using node 15 or 16 it is possible to generate the same prediction for X_6 according to X_1 ($X_6 = 68.5$). Besides, X_5 can be used as a predictor of X_6 if $X_5 \leq 9.2$ (node 17 and predicted $X_6 = 76.2$) and X_7 can be used as a predictor of X_6 if $X_7 \leq 280$ (node 21 and predicted $X_6 = 98.558$).

Evaluating second branching totally, since node 13 has the closest value to target value among 6 nodes (10, 13, 15, 16, 17 and 21) it can be concluded that X_8 can be used as predictor of X_6 when the variable X_8 is in the range of 133.4 and 180.

While considering the third branching, X_5 can be predictor of X_4 for $5.6 < X_5 < 7$ (node 27 and predicted $X_4 = 46.667$). Besides, X_4 can be used as a predictor of X_1 if $X_4 \leq 19.5$ (node 34), X_1 can be used as a predictor of X_5 if $X_1 \leq 455$ (node 37 and predicted $X_1 = 66.6$), X_8 can be used as a predictor of X_7 if $X_8 > 265$, (node 41 and predicted $X_7 = 92.5$), X_2 can be used as a predictor of X_1 for $82 < X_2 < 101$, (node 46 and predicted $X_1 = 111.800$),

Furthermore, we have two more branching. In the fourth branching there are three alternatives: X_5 can be predicted according to the value of X_1 (for $X_1 \leq 42.7$, node 49 and predicted $X_5 = 55.5$), X_1 can be predicted according to the value of X_2 if $X_1 > 70$, (node 52 and predicted $X_1 = 111.333$) and X_7 can be predicted according to the value of X_1 if $X_1 \leq 319.2$ (node 53, and predicted $X_7 = 114.5$).

In the last branching, we have two alternatives: either node 56 or 58 can be used for the prediction of X_1 , depending on the values of X_4 ($X_4 \leq 22.2$, node 56 or $X_4 > 36$, node 58 and predicted $X_1 = 111.800$).

By the term predictor, it is meant that the value of the independent variable can be forecasted from the value of dependent variable based on some specific conditions.

5. Conclusion

Material planning is one of the fundamental functions of most of the companies. While material planning is considered as a very important function for manufacturing companies, it is also very important for the service companies, especially for hotels. Although there are lots of inputs for hotel companies, the cleaning materials are not taken into consideration since it is thought that the cost of these materials are too low comparing by other inputs like food. In service sector, especially in hotels, the cleaning process is one of the fundamental activities for the satisfaction of the customer and cleaning and tidiness are essential factors for it. In the case of lack of cleaning materials, the cleaning

process cannot be done as it is supposed to do and this will cause a lot of problems in the management of hotels. For the proper cleaning process, the right cleaning material must be in the right place in time. This requirement can be achieved by material planning.

In this study, a five star hotel is taken as a case. In the case, hotel is observed for cleaning process for one month. During the observation the types of materials used for cleaning and their amounts are examined and documented. There is no systematic material planning for the cleaning process and no historical data about the cleaning materials used. By one month observation the types of the cleaning materials used and amounts of them were determined. This study is done to collect data for the cleaning process in the hotel and the study is just done as a beginning for material planning. The amount of cleaning material usage and the relations of these materials with each other are important inputs in the material planning process. Before the analysis started, one month observed data is bootstrapped in order to increase the reliability of the study.

In the study, it is determined that cleaning material X_6 (room cleaner) is the most used cleaning material among others. Then, the next most used cleaning material is X_1 (anti-quicklime). So, X_6 is the most important and critical material for material planning and requires more attention than the other cleaning materials. As it is shown in Figure 1, the usage of the cleaning material X_6 is relatively much more than the others. For the results of this study, CHAID algorithm is used.

In general, CHAID is used for nominal variables to categorize data and one of the data mining tools. However, in this study continuous variables were used in CHAID algorithm to predict dependability and the most used material (s). This study is a good example for the usage of CHAID algorithm as a data mining tool for the collection of inputs used in material planning in hotels. In this study, this data mining tool, CHAID algorithm, is not used for the classification of data, instead it is used for the determination of predictors which are dependent variables. These predictors are used for the prediction of independent variables when there is no data about them. Therefore, this will be helpful and supportive for the planning of cleaning material.

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Appendix.1 Decision Tree