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ADEM: An Online Decision Tree Based Menu Demand Prediction Tool for Food Courts

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Abstract. The uncertainty of consumption demand in institutional food courts can cause loses of resources, work power and prestige. In this study, to overcome this problem, decision tree, a predictive data mining method was utilized. Thus, decision tree models sourced from an original 44 monthly dataset were generated and a tool named ADEM was designed and developed to make online prediction against the best model. To determine the best model, 10 fold cross validation technique was applied. As a result, decision tree models reaching up 80.78 accuracy levels (VAF value) were obtained and a user friendly, platform independent and reusable decision tree based decision support tool is presented for managers and nutritionists.

Keywords: Decision trees, food demand prediction, data mining, demand prediction.

1. Introduction

The definition of “catering” is defined as the act of supplying food and related services in means of preparing, providing, delivering and serving; or preparing [1]. Several catering factories and institutions serve menus to customers which vary in each day. As the demand for the food is certain in many cases, in some institutions like universities, hospitals, etc. the demand for the menus may vary for different kinds of reasons. Therefore, this process has uncertainties in economics point of view. As stated in [1], if the actual demand cannot be foreseen correctly this either causes prestige loss (if demand is much than supply) or waste of resources and work power (if demand is less than supply). At this point, demand forecasting concept arises. As stated in [2] demand forecasting helps companies in several apparent areas, such as production, scheduling and customer service. Furthermore, Mike Hennel in [2] states that, being able to rebalance or reclassify inventory as a result of improved forecast accuracy can produce significant improvements in customer service without an increase in overall inventory value. Moreover as Bozkir and Akcapinar Sezer point out, approaches which forecast the demand for a served menu can present many benefits to institutions as it would optimize the balance of supply and demand in name of saving resources and work power [1]. At this point, Sundararajan et al. address the importance of information technology and services, computer aided tools providing intelligence to make real time decisions [3]. With this motivation, Sundararajan et al. implemented a decision support system for making operational decisions in food processing industry which is based on optimization techniques and focuses on determining optimum production scenario for every week based on the tradeoffs between service levels, inventories, costs and capacity [3]. As another example, [4] investigated the factors affecting menu demand in universities by employing decision tree method which is a member of predictive data mining methods family. Moreover, in [1] three decision tree methods, CHAID (Chi-squared Automated Interaction Detection), CART [5] (Classification and Regression Trees) and Microsoft Decision Trees [6] are employed to predict menu based food consumption demand in food courts and their performances are compared.

Demand prediction and employment of intelligence methodologies such as *data mining* or *soft computing* is not a new type of research in demand prediction. If literature is reviewed, several studies addressing different aspects of demand prediction can be found. For instance, Altunkaynak *et al*. [7] employed Tagaki-Sugeno fuzzy logic method aiming prediction of future monthly water consumption

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demand for Istanbul. Similarly, Abiyev *et al.* [1]-[8] investigated the feasibility of neural network based fuzzy inference systems for electricity consumption prediction by presenting a system for Northern Cyprus.

However if demand prediction literature is reviewed in food and nutrition point of view, a limited number of the studies can be found according to our best knowledge. For instance, Bhattarcharyya *et al.* [9] utilized time series method to forecast daily demand of perishable ingredient for a worldwide fast-food restaurant by presenting how Box-Jenkins seasonal ARIMA time series models can be used to reveal outliers in demand [1]. Besides, as stated before Bozkir and Akcapinar Sezer in [1]-[4] investigated the feasibility of decision tree method in food consumption prediction and achieved successful prediction results. However as pointed out in [4], the quality and richness of training data becomes very important in this kind of studies.

Data mining, on the other hand, is described as the utilization of intelligent algorithms and methods to extract hidden relationships, trends, correlations and associations in historical data. Although it involves several methods such as genetic algorithms, Bayesian networks, decision trees, support vector machine; data mining techniques are classified into two categories: predictive data mining and descriptive data mining. As the main aim of descriptive data mining is to reveal hidden nature of data, predicting future cases based on past examples constitutes the fundamental purpose of predictive mining [1].

In this study, a web based data mining oriented menu prediction tool named as “ADEM” is designed and implemented. Furthermore, it is equipped and tested with a 44 months period dataset containing records of food courts in Hacettepe University of Turkey. During the model building step, decision tree method is employed. As the previous studies [1]and[4] point out, decision tree method is a good candidate for some reasons:(1) ease of understanding and interpreting, (2) model transparency, (3) rapid model building, (4) on the fly prediction and as the last one (5) reasonable prediction accuracy. Therefore, Microsoft Decision Trees [6] algorithm and related framework is employed throughout the study. By this study, it is aimed to present a decision support tool for food court managers and also nutritionists to forecast future menu demands and enable them to form daily, weekly or monthly plans by considering the predictions. One another advantage of proposed system is to not only predicting previously served menus also new combinations and unseen menu items.

2. Data and Methodology

In this study, to constitute data mining models for prediction, a dataset which contains Hacettepe University food court daily menu sales covering 44 months is employed. The dataset which covers daily sales records for students, academics and officers starts from 1.1.2008 and ends at 21.8.2011. The dataset contains discrete, boolean and continuous valued attributes. The discrete valued attributes listed as follows: *food1, food2, food3, food4* (these are the names of foods presented in the menu). On the other hand; *day, month, calorie, sales count of academics, students and officers* constitute the continuous valued attributes. Besides, by applying a pre-processing on menu items, two extra binary (yes/no) features named *containsDessert* and *containsMeat* were extracted. With the help of these attributes, it was tried to be revealed whether or not vegetarian menus have any effect on menu sales as well as dessert contained ones. With a prior investigation, *isHolidayDay* binary feature was also extracted by checking each day on calendar to be used as a powerful feature.

Microsoft Decision Tree (MSDT) algorithm which is shipped with Microsoft SQL Server Analysis Services [10] was employed throughout the study. MSDT is designed for classification and regression tasks and mainly employs Shannon’s entropy as tree splitting criteria. Tree splitting and growing concept is the main point affecting generalization capacity of decision trees, thus it must be set precisely. In contrast to other some well known algorithms such as CART, MSDT does not offer any pruning step in tree induction stage. Nevertheless, it presents a parameter named “complexity_penalty” for controlling the growth of tree. MSDT also presents automatic feature selection, automatic binning and cardinality reduction features which makes it preferable than the other decision trees algorithms. However, the main reasons why we chose MSDT can be listed as (1) API (Application Programming Interface) support on .NET framework and ADOMD (ADO with multi dimension) extensions which enable programmers to create their third party applications talking to Analysis Services data mining engine and (2) dependency networks which visualize important features .

Prior to the decision tree model building phase, all cases were checked against syntax error and some foods which are pointing same type were aggregated and named as one common name. Overall dataset contains 1323 cases and 92 cases belong to March 2011-May 2011 months were kept as validation dataset and removed from training/test dataset for further validation. Remaining 1231 cases were shuffled and divided to 10 equal sized %10-%90 test-train partitions for 10 fold cross validation. Features on sales counts were selected as "predict" features while the remaining ones were set as input features. As the first step, most optimum *complexity penalty (CP)* value was tried to be determined by applying 10 cross fold validation tests (each for students, academics and officers) with 0.4, 0.5, 0.7 and 0.85 CP values respectively. Thus, 120 different decision tree models were obtained. In MSDT, the higher CP value causes shorter trees and vice versa. Each fold was tested against its test data with these four CP values and VAF (Variance Account for) results were gathered together. In this study, variance account for VAF (Eq. 1) index is used to check the prediction performance of models.

$$VAF = \left[1 - \frac{\mathrm{var}(y-y')}{\mathrm{var}(y)}\right] \times 100 \tag{1}$$

Where y and y' are the observed and predicted values respectively. The highest VAF valued CP is voted as the best CP for each fold. In Table. 1, it can be seen that "0.5" is the best CP over 10 fold cross validation.

Table. 1: Frequency table of complexity penalty parameter over 10 cross validation.

Complexity Penalty Value	# of times it is winner
0.4	3
0.5	6
0.7	2
0.85	1

On the other hand, 7th fold with CP = 0.5 was detected as the best models to represent our prediction tool. Due to limited number of pages in this study, the results of VAF values could not be given. However the VAF values of the 7th fold models (CP=0.5) can be listed as: students = 80.78, officers = 80.58, academics = 64.81. According to dependency network results, it can be deduced that *month*, *is HolidayDay*, *containsMeat* and *containsDessert* features highlighted as the first four important variables in all three kind of customers.

3. The details of ADEM

As stated before, the main point of this study is to design and implement of a decision tree based decision support tool. Following to model processing and determination of the best one, ADEM was developed at the second stage. Ease to use and platform independence were selected as the main design considerations. Therefore instead of desktop application model, web-based approach was preferred.

As can be seen on figure 1, ADEM is built as a three tier application. Data mining engine in Microsoft Analysis Services constitutes the *data layer* and this layer is responsible of managing data mining models manipulated by domain experts. On the other hand, ADEM contains two important modules: (1) decision tree explorer/viewer and (2) online query module. These modules were designed for cross browser compatibility which enables it to be run on either desktop or mobile devices regardless of the operating system. ASP.NET [11] framework is mainly employed in ADEM.

In the first module (Fig. 2) decision tree explorer, managers have the ability to check models and understand the important factors (features) affecting demand prediction. In this module, an expandable tree viewer employing Walker's algorithm is used. In the second module, users have the ability to make visual queries against to mining engine through ADEM. The only need is to specify which type of customers (academics, students, officers) should be predicted and input the parameters (food1, food2, food3, food4, month, day, is that day holiday, does this menu contains dessert or meat) Then with just one click, daily demand prediction results are retrieved and listed as a table on user interface.

The same as all predictive data mining models have, decision trees has also prediction errors. Therefore, with the actual demand prediction, variance, standard deviation, probability and support values can also be retrieved for managers to have insight on uncertainty. On the other hand, one another unique advantage of this tool is to predict the daily demand even for not served menu combinations so far. Thus, managers or nutritionists will have the ability of making trials on different menu combinations for different purposes.

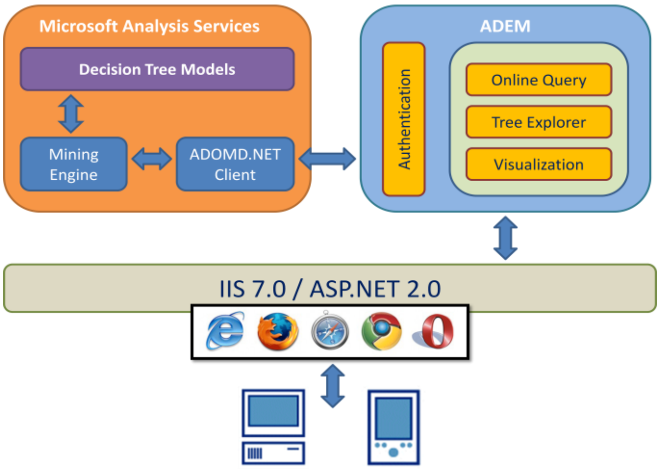

Fig. 1: System architecture of ADEM

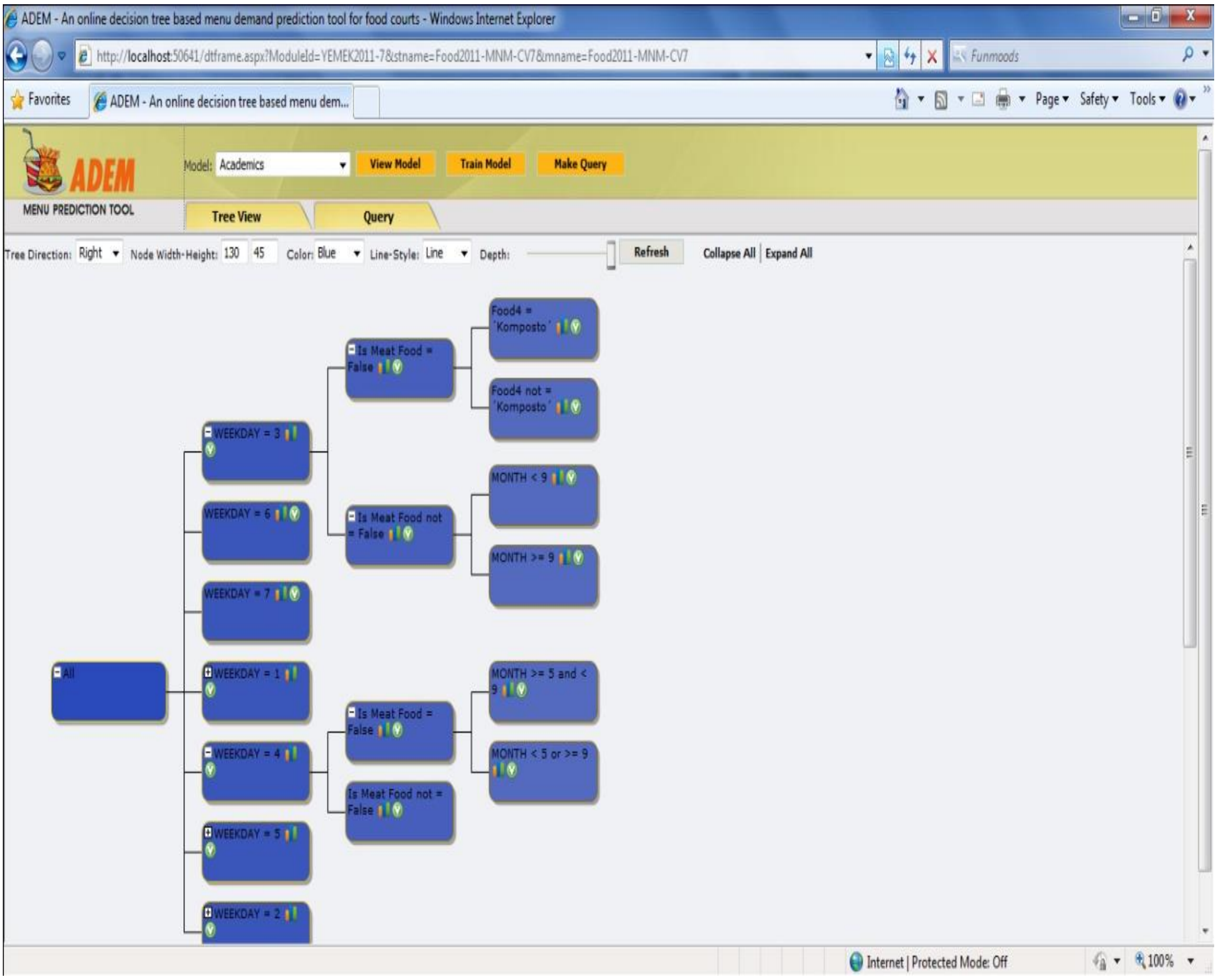

Fig. 2: Decision tree explorer

On the other hand, ADEM is not designed statically. In other words, this tool is capable to be run on different decision tree models. This means that, with different types of datasets can be modelled on Analysis Services and then ADEM can load and interact with them through general ADOMD.NET functions.

4. Conclusions

In this study, a web based decision support tool named “ADEM” a menu demand prediction for food courts was designed and developed. On the other hand, an original 44 months period dataset containing sales numbers of three customer types and menu related information was employed during decision tree model generation. As the previous studies have shown that, decision tree models are easy to interpret and present accurate prediction results [1]and[4]. Therefore, instead of black box type of methodologies (e.g. artificial neural networks or support vector machines) decision trees are employed in prediction models. As success of models shows that, it has been a good candidate model for these types of tasks. To be further used in ADEM, the most successful model that has best generalization/prediction capacity is tried to be determined. In order to achieve this goal, optimum tree depth is searched by testing different *complexity penalty* parameter. According to results, 0.5 is determined as the optimum value.

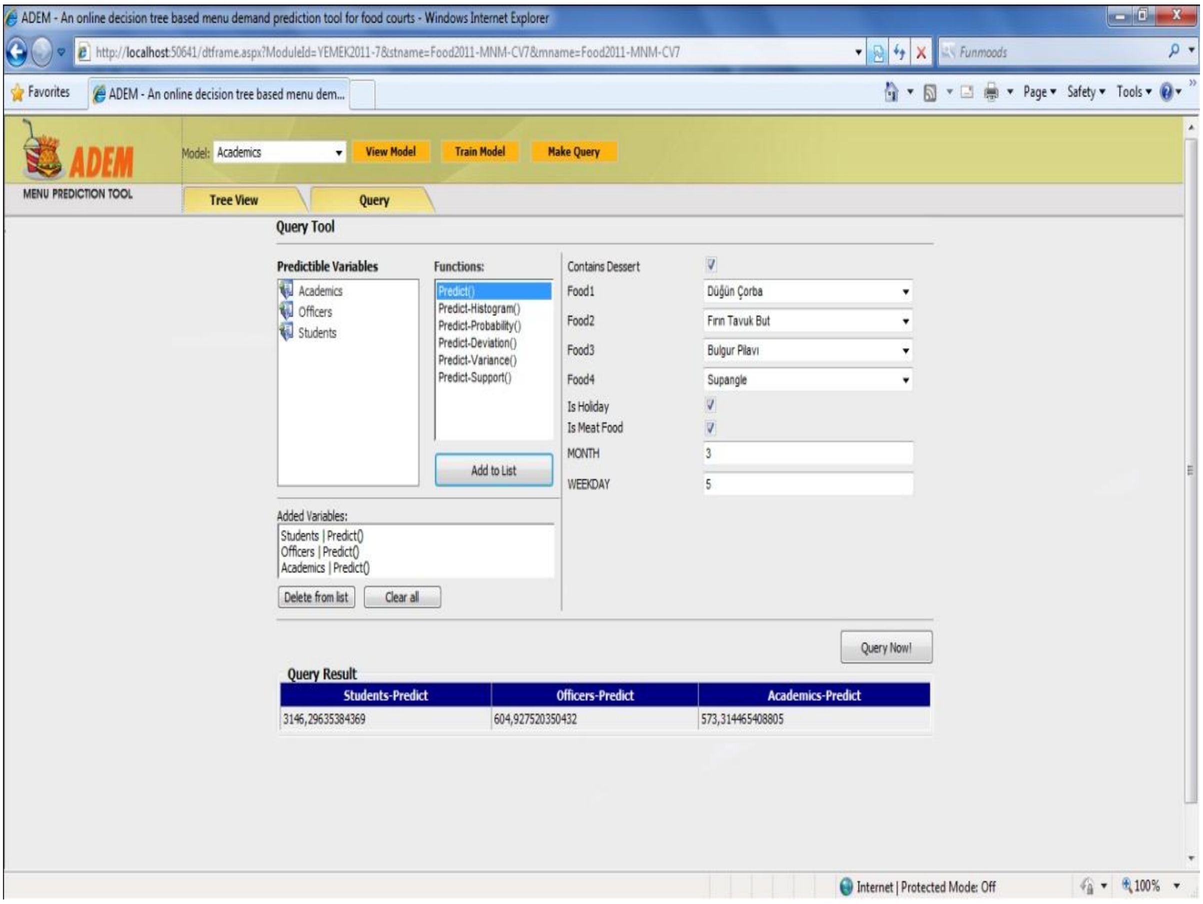

Fig. 3: ADEM query page

In this type of data driven studies, the quality of data is coming to prominence. Therefore, to get better results it is highly recommended to avoid noisy data. Seasonal fluctuations constitute the noisiest cases. Therefore, it is highly advised to remove these periods at pre-process stage of whole data mining process.

On the other hand, it is discovered that non vegetarian menu combinations are demanded much more than vegetarian ones. This finding can vary in different cultural habits. However, since it is one of the most important features, extraction and employment of this type of pre-processed features highly recommended for better prediction accuracy.

By this study, consumption prediction of menu combinations which not served yet, also become possible. Therefore with this achievement, it is believed that managers of institutional food courts gain more power in short term decision making.

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