Data Mining Through Data Visualization: A Case Study on Predicting Churners on Telecommunications Data Set

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Abstract—Data mining is the process of extracting meaningful information from a large, raw data. These processes are carried out by various, detailed methods. And, the obtained results are used to make various interpretations and to draw conclusions. Deductions can either be made by interpreting the data after various operations or by plotting the data in various forms of graphs. This type of interpretation over graphics is called data mining through data visualization. Generating graphs that can be used to draw various conclusions on a telecommunications data set with the help of some packages included in the R program is presented in the paper. It does not require upper-level math skills to interpret these graphs; and everyone having knowledge about the industry and data set of the graphs has the ability to plot similar graphs and make analysis and interpretations regarding the results obtained on the data set at hand. In this study, R language was preferred as the software infrastructure for data mining applications, and graphs were plotted for interpretation through data visualization with data mining.

Index Terms—Data visualization with data mining, R, Telecommunications.

I. INTRODUCTION

Nowadays various data mining methods are being used to turn large and complex data into usable form of data. Applying these methods requires a certain amount of time. However, the numerical results obtained as a result of these analyses cannot be interpreted easily by everyone. In order to make sense of these results, analysis graphs are plotted to draw conclusions. In this way, interpretations on telecommunications data set is performed using graphs, without any analysis made through the data mining methods. With these graphs, it is aimed to make some deductions that need to be considered in terms of advertising campaigns and campaigns in the telecommunications industry, without even needing an in-depth analysis of the data.

In important situations such as presentation and in-house auditing, it can be difficult to access information on complex tables instantly, and it can be difficult to explain the data in the table to the audience. In such cases, visualization of the data to be acquired from the tables provides both convenience and effectiveness in business. This is possible thanks to the graphs plotted through visualization and data mining. In this study, the plotting of the graphs that can be used to draw various conclusions on a telecommunications data set was explained with the help of the packages included in the R program. It does not require upper-level math skills to interpret these graphs; and everyone having knowledge about the industry and data set of the graph has the ability to plot similar graphs and make analysis and interpretations regarding the results obtained on the data set at hand [1].

II. DATA MINING

There are various definitions of data mining. One of the mostly used definitions is obtaining usable information from complex data [2]. Data mining, or the knowledge discovery as called in the literature, is the process of extracting potentially useful and beneficial information in the complex and vast amounts of data. During this procedure, multiple scientific study fields are used. These fields of study are the data management systems, statistics, artificial intelligence and machine learning. The knowledge discovery on the data by combining all these fields together is called data mining [3]-[5]. In short, data mining is the search for relationships and rules in vast amounts of data using computers that will allow us to make estimations about the future [6].

III. VISUALIZATION OF DATA WITH DATA MINING

Data visualization is the gathering of complex and scattered data in the classical format and presenting them in an understandable and interpretable forms through easily identifiable visuals or graphics.

Schematic structures can be abstracted while visualizing the data. Visual elements such as tables and graphs can be used to provide a clear information flow. Thus, cognitive processes such as comparison, interpretation and analysis can be performed more effectively and efficiently [7].

In parallel with technological developments, a continuous increase in the data size is observed. As a result of this
increase, it becomes very difficult to extract meaningful and usable information from the data. Especially the subscriber-based companies such as telecommunications, banking, insurance and etc. aim to obtain profitable and efficient information by using the data at hand. For this reason, subscriber-based companies have data analysis departments or outsource this service to data analysis companies. The work done by these departments is to perform visualization by plotting graphs that employees in each unit of the company can understand. By means of data visualization, the data become meaningful without requiring knowledge of mathematics and statistics to interpret the data in an efficient and easy manner.

IV. CUSTOMER CHURN ANALYSIS

In subscriber-based industries, the analysis carried out to prevent loss of existing customers is called churn analysis. It is a method of analysis that is typically used in telecommunications, banking or insurance industries for predicting the churn of current customers so as not to lose the customers. Thanks to these estimates, solutions can be generated within the scope of customer relationship management (CRM) to prevent customer churn. In the literature, the terms customer attrition, customer churn, customer turnover, customer defection are also used for the same concept Customer churn is of great importance in the subscriber-based industries such as telecommunications, banking, and insurance, because retaining existing customers requires lower cost than gaining new customers in general [8].

V. THE TELECOMMUNICATIONS DATA SET STUDIED

The telecommunications data set includes 8000 customer records and 20 variables which has been taken from one of the major telecommunications company of Turkey for a period of 10 months. The names, explanations and data types of these 20 variables are shown in Table 1.

| Attribute       | Description                                              | Data type  |
|-----------------|----------------------------------------------------------|------------|
| age             | Age                                                      | Numerical  |
| age_of_line     | Customer lifetime duration                               | Numerical  |
| tariff_type     | Tariff type (Postpaid, Prepaid)                          | Nominal    |
| device_type     | Device type (Smartphone, Laptop, etc.)                   | Nominal    |
| last_reload_year| Last reload date (for Prepaid subscribers)               | Nominal    |
| mmo_count_07    | Monthly number of conversations with its own subscribers (Call) | Numerical  |
| mmo_duration_07 | Monthly talk time with its own subscribers (Call)        | Numerical  |
| mmt_count_07    | Monthly number of conversations with its own subscribers (In call) | Numerical  |
| mmt_duration_07 | Monthly talk time with its own subscribers (In call)     | Numerical  |
| mmo_non_count   | Number of Monthly Calls Made with Other Operators (Call) | Numerical  |
| mmo_non_duration| Monthly Talk Time with Subscribers in Other Operators (Call - min.) | Numerical  |
| mmt_non_count   | Number of Monthly Calls Made with Subscribers in Other Operators (In call) | Numerical  |
| mmt_non_duration| Monthly Talk Time with Subscribers in Other Operators (In call) | Numerical  |
| mmt_total_count | Number of Total Monthly Calls (Call)                     | Numerical  |
| mmt_total_duration| Monthly Total Talk Time (Call)                       | Numerical  |
| mmt_total_count | Number of Total Monthly Calls (Call)                    | Numerical  |
| mmt_total_duration| Monthly Total Talk Time (In call)                     | Numerical  |
| mmmo_duration_07| Number of SMSs per month                                | Numerical  |
| callcenter_count_07| Monthly Call Center Complaints Call Count           | Numerical  |
| Churn_2013_07   | Subscriber churned?                                      | Binary     |

VI. CUSTOMER CHURN ANALYSIS APPLICATION THROUGH VISUALIZATION

In this study, the plotting of the graphs that can be used to draw various conclusions on a telecommunications data set was explained with the help of the packages included in the R program. It does not require advanced-level analytical skills to interpret these graphics; and everyone with professional knowledge on the issue and industry can plot similar graphs and make analysis and interpretations regarding the results obtained on the data set at hand.

In this section, a study on density and violin graphics with the help of the R graphic packages will be discussed [9]. In plotting these graphs, customer lifetime and churn status in a telecommunications operator were grouped and interpreted according to categorical attributes.
A. Graphics Obtained By Density Graphics

In this section, interpretations on the density graph obtained with the ggplot2 package of the R is discussed.

Figure 2 shows the churn status of the customers of female, male and unknown gender. According to the graph in Figure 2, churn status yes (Y) of males (M) is more instable than females (F). It is seen that none of the subscribers with unknown gender information churned (N).

The interpretation that can be made on the graph in Figure 3 is that users over 65 years of age do not churn (N) and use their phones only for making calls. There is a continuous fluctuation in the 16-24 and 25-44 age groups, and it can be said that they probably use smartphones and are looking for various campaigns.

Figure 4 shows that the rate of churn is higher in prepaid subscribers than the postpaid subscribers. This may be due to long-term contracts of postpaid subscribers.

B. Graphics Obtained By Violin Graphics

In this section, interpretations on the violin graph obtained with the ggplot2 package of the R is discussed.

It is seen in the not-churned (N) section of the graph in Figure 5 that the churn of subscribers with unknown gender and male subscribers was more unstable than the churn of females. A similar interpretation is also made in the density graph.

The graph in Figure 6 shows that users who are over 65 years old are less likely to churn and that they only use their phones for making calls, similar to the interpretation of the density graph. There are various fluctuations in other age groups. Customer churn (Y) is observed to be low in young people in the 16-24 age group compared to the ones in the 25-44 age group.

In the graph in Figure 7, it can be seen that the tendency to churn (Y) is higher in prepaid subscribers compared to postpaid subscribers. This interpretation is observed to be the same in the density graph.
VII. CONCLUSION

The main objective of this study is to develop a data visualization application that allows to obtain interpretable graphs without being overwhelmed by data mining methods. In the study, the complementary and verifying results obtained by density and violin packages of the R software were presented by using a telecommunications data set.

In this regard, it is observed that everyone having knowledge about the industry and data set of the graph has the ability to plot similar graphs and make interpretations on the results obtained. Therefore, it is now quite easy to plot and interpret graphs suitable for any data set.

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