

Using Visual Analytics to Reduce Churn

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Abstract. The technological advance and the use of data for decision-making drive business and increase competitiveness among companies. They must understand the environment in which they operate and quickly respond to the needs of their customers, preventing them from canceling their services, maximizing profit, and benefit their own organizations. The main goal of this work is to present a visual analytics approach to deal with a large amount of unstructured, complex, and dynamic data and improve companies' ability to detect the probability of losing a client at an early stage. We processed the probability of subscription cancellation using the machine learning algorithm Random Forest, and we allowed similar customers comparison using the k-nearest neighbor's algorithm. Then, we developed two main visualizations: a general dashboard that displays the probability of subscription cancellation of each client and the variables that can influence this decision; and a radar chart that displays many quantitative variables and allows comparison with other similar customers. To validate our approach, we present a case study with a data set from a hosting services company that uses the Platform as a Service model. Through the application of informal interviews, we concluded that the provided visualizations helped teams in the process of reducing churn rate and therefore maintaining a growing customer base's company. Our visual analytics solution allowed the analysis and information understanding to create strategies and make assertive decisions for professionals involved in the retention process.

Keywords: Churn · Visual analytics · Machine learning

1 Introduction

The advancement of technology and the use of data for decision-making boost business and increase competitiveness among companies. In this context, companies must understand the scenario in which they operate and respond quickly to the needs of their clients. Thus, the focus becomes the customers, through the analysis of their behaviors, to prevent them from canceling their services [10]. The loss of loyal clients is a threat to companies in several sectors, so efforts should be directed more towards retaining existing customers than attracting new ones [7].

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For this, companies have teams responsible for the Customer Relationship Management (CRM) process, which aims to manage customer information to maximize their loyalty [11]. Its main objective is to satisfy customers to prevent them from canceling their services. For the Platform as a Service (PaaS) market, which provides infrastructure and technology for the development and hosting of applications, the turnover rate, or churn rate, is one of the main metrics to assess business performance. Churn is a marketing term in which the customer is interested in another organization or product [2].

One challenge is to reduce cancellation requests and prevent the customer from reaching that decision. Therefore, it is essential to understand the factors that motivate you to request cancellation. The ability to detect the probability of losing a customer at an early stage is something that every company wants to achieve [3]. However, within a large customer base and with a significant number of variables, it is complex to identify patterns and factors that influence cancellation requests. Analyzing data from various sources of information promises to address answers to these questions. However, this analysis requires data integration, which is difficult for users without software development skills [4].

According to Keim et al. [8], visual analytics is an interdisciplinary research area that combines, among others, visualization, data mining, and statistics, making the way of processing data and information understandable for an analytic discourse. Therefore, the use of visual analytics [3] can be an alternative to assist in the analysis of a large amount of unstructured, complex, and dynamic data, supporting the retention function. In this context, tools and techniques are created to allow people to synthesize and obtain information from this kind of data, detecting the expected and discovering the unexpected.

Thus, the main goal of this work is to present a visual analytics approach to support CRM teams to create strategies and act at the right time, that is, before a customer request a service cancellation. Our prototype implementation allows analyzing different data sources and identifying the variables that affect customer cancellation through interactive graphs and statistical data. Our main contributions are:

- The provided visualizations that allow analyzing the probability of subscription cancellation of each client, as well as to compare the similar ones;
- A high accuracy of the used data mining algorithms;
- The possibility of using the approach with your own data sets;
- The validation of the proposed approach through a case study that shows how it helps to reduce the churn rate.

The remainder of the paper is organized as follows. Section 2 presents some related work. The proposed approach is described in Sect. 3. Section 4 details the obtained results through the presentation of a real case study and the feedback obtained with an informal interview with domain experts. A discussion about the future work directions is also presented. In the last section, we outline our conclusions.

2 Related Work

There are several works already developed involving the study of prediction models for churn and client loyalty based on ML (Machine Learning) methods. Noyan and Simsek [12] and Zakaria et al. [17] conducted studies to understand customer loyalty. The first [12] revealed that clients' loyalty depended on price, discount, product quality, service quality, perceived value, and satisfaction, with customer satisfaction being the most important factor influencing their loyalty. The second [17] concluded that the store's partnership program, premiums, insurance, discount, and price had a significant impact on customer satisfaction and loyalty.

An approach to better understand clients' behaviors and classify them based on the RFM (Recency, Frequency, Monetary Value) and LTV (Life Time Value) model using genetic algorithm for the analysis was presented by Chan [1]. Thus, the customers with the highest value could be identified for the recommendation programs. Qureshi et al. [15] used ML techniques, such as regression, RNA (Artificial Neural Network), and decision trees, to predict churn for telecommunications customers. The results showed that decision trees had the best performance to identify potential churners. In the study by Khodabandehlou and Rahman [9], five variables were added to the RFM model, with emphasis on discount, delivery time, and price. An accuracy of 97.92 was obtained compared to the specific use of RFM, using the RNA method with the highest performance.

Table 1 presents the comparison between studies involving churn and ML techniques. We note that the variables of the RFM model are widely used in retail, and the price variable is used in almost all situations. In telecommunications, with a more focused aspect to services, customer behavior is used. Decision trees are used in different scenarios, but studies show that it is necessary to analyze each need and test more than one technique to find the best results.

Table 1. Comparison between churn studies and ML techniques.

Ref.	Variables	Techniques	Sector
[12]	Price, discount, service quality, perceived value, satisfaction	SEM (Structural Equation Modeling)	Commerce (supermarkets)
[17]	Store's partnership program, premiums, insurance, price	Decision tree, boosting, logistic regression	B2B/retail
[1]	RFM	Genetic algorithm	Retail resale
[15]	Customer behavior, such as call time	Regression, RNA, decision tree	Telecommunications
[9]	RFM, discount, delivery time, price	RNA	Commerce

The study by Dintakurthi [3] is the closest to the objective of this work. Through the analysis for the manufacturing industry, they identified the variables that affected churn and developed a model to support the after-sales functions. As a result, they made available geolocation graphs indicating places where there is more churn and helping in decision making, for example, identifying the regions where should be prioritized attention to churn. Bar and line graphs are also available to show the distribution of transactions and their relationship to churn and the impact of the price on churn.

Grammel [4] provided support to end-users when analyzing multiple data sources. They used Tableau to explore a widget-centric approach to data analysis and integration. Oelke et al. [13] presented techniques for analyzing positive and negative opinions expressed by customers. They developed visual analytics solutions to support analysts. An example is the interactive circular correlation map that offers a detailed view of the data and allows you to find correlations between the different aspects of the data set. Park [14] presented a visual analytics tool that reads a variety of textual data sources and extracts important keywords, relationships, and events using ontology and natural language processing methods. It provides users with an integrated and interactive search interface to facilitate data investigation. The keywords are aggregated according to the date and the news where they were published.

Table 2 presents a comparison of the works that support users' functions. This table shows that there are several charts available for each need and that the combination of one or more interactive graphics is an important practice for churn analysis.

Table 2. Summary of visual analytics studies.

Ref.	Objective	Chart/Visual model
[3]	Predict churn and support after-sales functions	Geolocation, bar, and line chart
[4]	Support end users in data integration	Cognitive support structure widget-based
[13]	Support CRM analysts	Interactive circular correlation map
[14]	Provide an integrated and interactive research interface for investigation	Bubble chart/keyword cloud

Among the nine works covered, only four present visualization techniques that support end-users. In five works, studies were carried out with different types of techniques, using multiple variables. However, none of them present a tool that supports the daily challenge of retaining customers that is constantly updated and interactive. Besides, none of them were made for the PaaS (Platform as a Service) or similar market. More than one study used variables based on the RFM [1,9] model, but none analyzed these variables based on customer

interactions by text, such as chat and call systems. Therefore, we identified the opportunity to combine predictive techniques with visual analytics to support customer relationship teams, such as retention, which are updated daily according to client's behavior and the market.

3 Visual Analytics Approach

The following subsections describe our visual analytics solution to support and improve the productivity of CRM teams that work with retention and aim to reduce churn. Through interactive graphics and statistical data, it allows the analysis of customer, product (CRM), and attendance data to identify the variables that affect cancellation. The developed prototype can be used by all companies that adopt a business model based on services, mainly PaaS, Infrastructure as a Service (IaaS), and Software as a Service (SaaS).

To perform some tests and to facilitate the definition of the classification algorithms to be adopted, we initially used Weka[1]. After that, we selected the following tools to automate, create, and integrate these algorithms with other systems: Language Python[2] for the collection, preparation, and pre-processing of data; and Language R[3] and Shiny[4] for the implementation of the visualizations techniques and the web application. CSV (Comma-Separated Values) files are accepted as data entry and the MySQL database[5] was used for persistence and maintenance of the data warehouse.

3.1 Research Methodology

We started developing our approach with data entry definition, including source and variables identification and data preparation. Then we plan the data processing by identifying the algorithms that could be used to create the statistical and predictive models. Finally, we specify the interactive visualization techniques that would be implemented. Figure 1 presents an overview of the development methodology.

3.2 Data Input

Data preparation can be divided into three stages: source identification, collection, and preparation. The identification of data sources was made by analyzing the systems and databases used by the team responsible for the CRM process in a PaaS company, whose main product is the website hosting service. Thus, seven main data sources were identified to obtain the variables used for model creation. Table 3 shows the list of identified sources. A set of 42 variables was identified,

[1] https://www.cs.waikato.ac.nz/ml/weka/.
[2] https://www.python.org/.
[3] https://www.r-project.org/.
[4] https://shiny.rstudio.com/.
[5] https://www.mysql.com/.

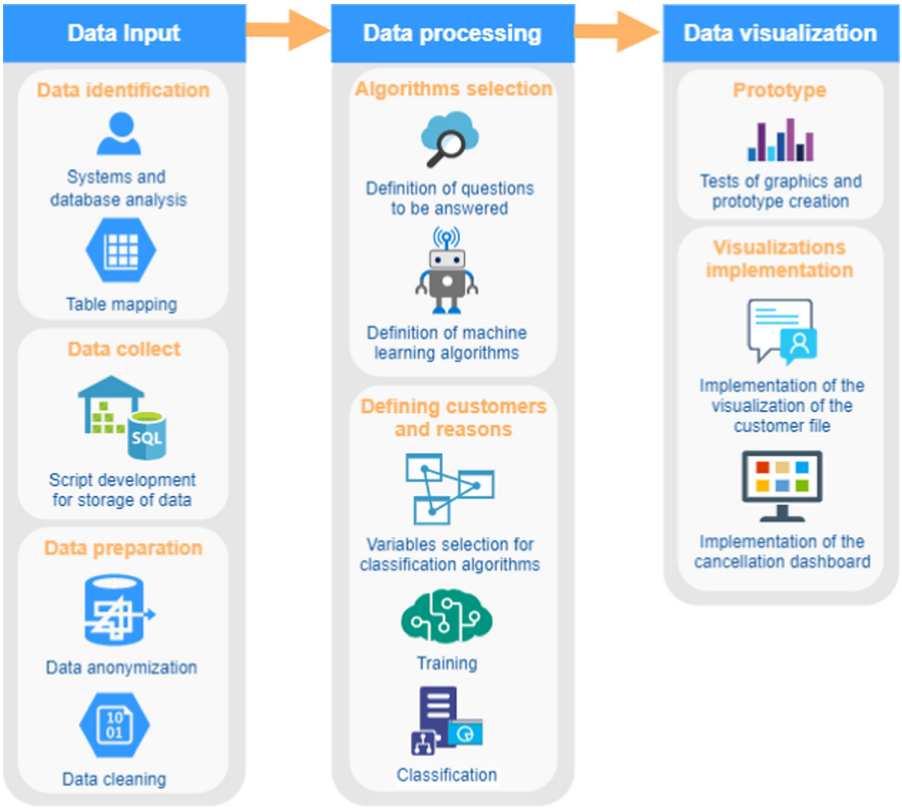

Fig. 1. Work development methodology.

Table 3. Table of data sources.

Source	System	Technology
Customers	CRM	MySQL
Products	CRM	MySQL
Calls	Backoffice	MySQL
Phone calls	Asterisk	MySQL
Websites	Backoffice	MySQL
Financial	Senior	SQL Server
Cancellation	Backoffice	MySQL

such as Lifetime Value, Client Status (active, blocked, debtor), Contracted Plan, Total Contacts and Average Response Time, and access to the control panel of the contracted service in the last 30 days.

Data collection can be done daily from different sources and made available in CSV files. A Python script reads the CSV files and stores their contents in a table structure in a MySQL database. The data preparation process includes anonymizing (for research purposes) and cleaning the data. For anonymization, sensitive information was suppressed through a cryptographic algorithm implemented while reading data. Data cleaning involves checking for missing or null data, special characters, and eliminating outliers.

3.3 Machine Learning Algorithms

To support the definition of the best strategy and algorithm to be used, we have defined two main questions to be answered:

- Which customers are most likely to request cancellation?
- What are the main variables that affect cancellation?

Therefore, we decided to use classification algorithms to identify customers with a high probability of cancellation based on their variables.

First, we selected a sample of data with canceled and active customers to create the model. After that, we defined the objectives concerning the metrics so that the prediction model has an accurate classification of customers with a tendency to cancel. We decided to use recall, precision, accuracy, and F-measure metrics to analyze the results of the algorithms. We then compared the results of two algorithms: Artificial Neural Network (ANN) and Random Forest. After reaching the desired precision, the model was integrated with the data visualization tool proposed to be made available to the teams.

Before training the predictive model definitively, we selected the variables to maximize its performance. Then, we configured the algorithms and performed some tests looking for accuracy of at least 80%. After reaching an accuracy of 81% with the Random Forest algorithm in Weka, we implemented it in Python using the library Scikit-learn[6]. The first step to obtaining a good result was to treat the categorical data by transforming them from string to numeric. The next step was to assemble the training and test data set. For a better result in the model creation, we defined the same number of canceled and active members, 2,000 each. The data set was then divided into training data (85%) and test data (15%). In the first run, all variables were used. For better accuracy, we included a code listing the importance of each variable and defined which ones should remain for the final model. With the optimization of the variables, we obtained an accuracy of 87%.

After we created the model, it was integrated with the data visualization tool. Thus, we were able to consult the data set in the MySQL database to be classified. Analyzing the obtained results, we verified a great variety of values in some variables, making it difficult to visualize their correlation. Therefore, we implemented a binning algorithm to treat the data and organize it on a scale from 0 to 100. To determine the cutoff values, we used the percentile

[6] https://scikit-learn.org/.

logic. For variables with a lot of variation, percentiles every 10% were used, and for variables with less variation, they were divided into 10%, 30%, 60%, and 90%. The results were then stored in the database for later consumption by the application responsible for data visualization.

3.4 Interactive Visualizations

Considering the questions to be answered and the objectives of the proposed work, we chose two main visualizations to help teams avoid cancellations. The first one is the visualization of a dashboard that displays the probability of cancellation for each customer and the variables that can influence this decision. The challenge in this visualization was to support a large amount of information easily and on a single screen. For this, we rely on the table lens technique [16], which allows an adequate visualization for the amount of data. In this visualization, illustrated in Fig. 2, each row represents a single record, and the columns represent a specific indicator. For its implementation, we use the LineUp.js[7] library together with R and Shiny.



Fig. 2. Retention dashboard.

The first column of Fig. 2 contains the customer's identifier, and the second contains the probability of cancellation. The other columns correspond to the

[7] https://lineup.js.org/.

several variables used by the machine learning algorithm to perform the classification. The numeric data is shown as a progress bar, and the strings are shown as text. Above each column (Fig. 2A), a histogram is displayed to provide an overview of how the data set is distributed. When selecting one or more lines, the numerical values are displayed within each bar.

Below the title of each column, three options are displayed. The first one (Fig. 2B) allows sorting in ascending and descending order. The second (Fig. 2C) offers the possibility to apply a filter through a free typing box. The third (Fig. 2D) opens the menu shown at the top right of Fig. 2. The first option of this menu allows each column to be sorted in descending, ascending, or random order. The second option enables the grouping of rows, for example, to divide the data into two groups, one with values above 50 % probability and the other below 50 %. The other options can be used to rename the column; change the colors of the bars; filter a range of data; change the display of the bars to alternatives such as absolute value, a symbol of proportion, or points; clone a column; and remove a column, allowing to focus on the data that most matters in the analysis.

The second visualization consists of a radar chart that displays the customer's data considering the quantitative variables of use of the services and allows comparison with other two similar customers. The similarity is determined using the k-nearest neighbors [6] data mining technique. Each variable has its own axis, and all axes are joined in the center, as shown in Fig. 3.

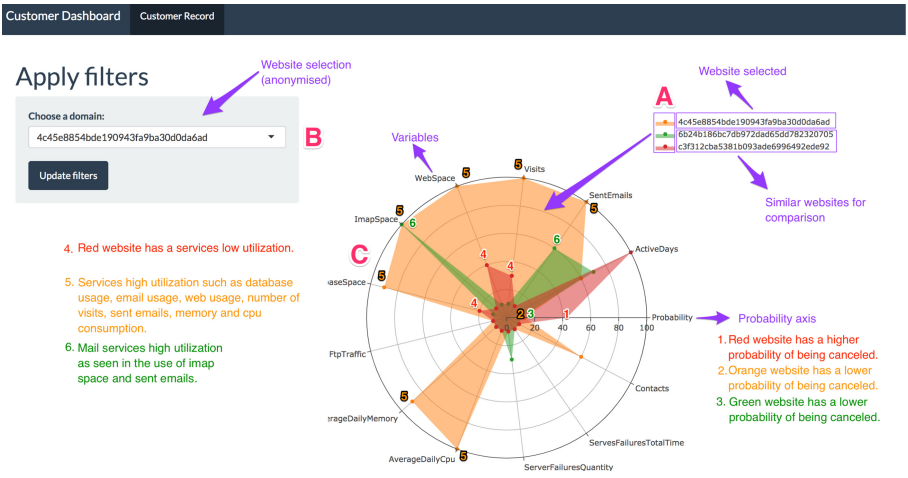

Fig. 3. Customer dashboard.

Each customer on the radar chart is represented by a different color, which is identified by a legend, as shown in Fig. 3A. Moreover, each customer can have their data visualization deactivated by just clicking on the legend line that has

its identifier number. It is also possible at any time to select a new customer through a selection list, as shown in Fig. 3B. Finally, it is possible to move the axes by clicking on a variable and dragging as desired, changing the positions of the variables as well as changing the original scale from 0 to 100 (see Fig. 3C).

In the example in Fig. 3, three customers with different cancellation probabilities are being compared. It is possible to observe that the customer presented with red color is who least uses the services and, consequently, is most likely to be canceled.

4 Case Study

In this section, we present some use cases to exemplify the use and potential of the developed approach. Also, to assess its functionality, the approach was made available for five weeks on an experimental basis to three industry analysts responsible for retaining the website hosting product within a PaaS company, the same one that made the data available to develop this work. The main contribution identified by the analysts was the possibility to quickly and easily perceive the probability of a cancellation and to analyze the values of the variables in a unique and interactive view. The goal was to act proactively before a customer request a cancellation. But, in practice, it also helped the team when trying to reverse a cancellation request.

4.1 Data Set

The data used in the case studies were collected and prepared as described in Subsect. 3.2. The selected data set contained information from 85,000 websites, but 1,338 website records were removed with the cleaning process. In this use case, it is considered that there was a cancellation whenever a website is canceled. However, a customer may have contracted one or more plans, and each plan will have an associated website.

4.2 Use and Availability of Services

A practical example occurred in a cancellation request in which the employee realized that the customer had little or no visit to his website, as shown in Fig. 4A. The client had hired a professional to develop a new website. However, it was unsuccessful and, therefore, did not use the service. Thus, an additional product, which allows people without technical knowledge to create a website, was offered, thus maintaining the customer. We noticed that the algorithm had an excellent assertiveness since the probability was indicated as 83.4%.

In general, they noticed a relationship between the use of services and the probability of cancellation. Analysts have identified situations where the more services are used, the less likely the customer will cancel. This finding had already been illustrated in Fig. 3, where the website represented with orange color has a low probability of cancellation and high use of services.

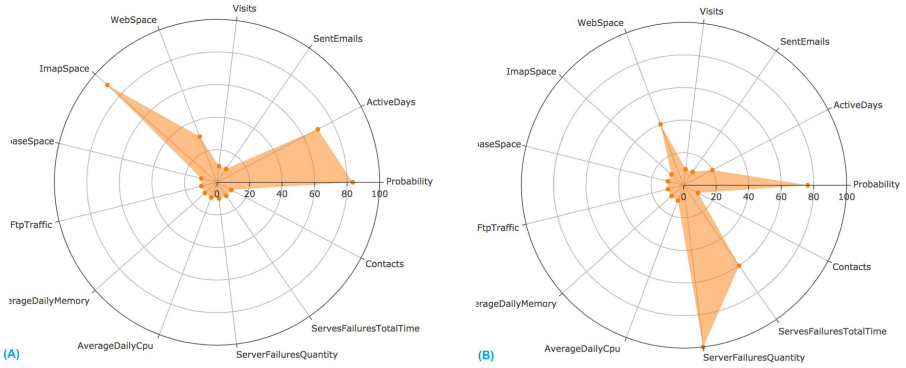

Fig. 4. Chart for reversed (A) and canceled (B) customer.

In another analysis, the sending of e-mails was compared with the cancellation probability. First, a filter was applied to the e-mail sending variable, selecting records with a value greater than 50. Then, only those records with a probability of cancellation, which is greater than 50%, were filtered. The result was the return of only 15 records, and the highest probability is 57%.

In another case, despite the failure to avoid cancellation, analysts were soon able to understand the motivation for the cancellation request through the use of our approach. As can be seen in Fig. 4B, there were many service availability problems as shown by the variables *ServerFailuresQuantity* and *ServerFailuresTotalTime*. The probability assertiveness was 78.1%.

In general, the retention dashboard allows the quick identification of the customers most likely to cancel, and the customer dashboard allows a more detailed analysis for each client or a group of similar clients. Through the case study, the visualizations available in our approach showed that the variables related to the availability of services, such as the number of server failures and the total time of server failure, can lead to the cancellation classification. In other words, it is necessary to invest in the quality of services, as its unavailability is directly linked to possible cancellations.

4.3 Net Promoter Score

The analysts identified that despite being a metric that measures how much the customer is the brand promoter and indirectly satisfied with the contracted services, the Net Promoter Score (NPS) did not influence the increase in the probability of cancellation for most customers. By analyzing the data using the retention dashboard, they observed that out of a universe of 83,662 records, only 600 were identified as retractors with a greater probability of 50% cancellation. When the filter is raised to a probability greater than 80%, only 3 records are displayed.

This result brought a certain surprise to the team that tested our visual analytics approach. They will continue to observe the behavior, but no strategy

has been defined for the moment. A situation that still requires analysis is that many records that do not have the NPS survey performed.

4.4 Discussion

We provide all the codes of our visual analytics approach at the GitHub[8]. Thus, it is possible to use it with other data and in different contexts, needing only to make an adjustment and new training of the machine learning algorithms according to the variables that will be used.

As lessons learned from the development of our approach and the case study carried out, we can list:

- The necessity to understand the difficulties of customers in using the service to encourage and retain them, which is facilitated by the use of the customer dashboard (Fig. 3);
- The importance to know the variables that most influence the probability of cancellation, which is facilitated by the use of the retention dashboard (Fig. 2);
- The strategy to proactively monitoring new customers through the proposed visualizations allowing to identify the need to assist in the use of the services because the more you use the services, the lower the chance of cancellation;
- Constant monitoring using the dashboards (Figs. 3 and 2) allows us to identify service failure situations, which can then be adjusted with a focus on recovering customer confidence.

One limitation we faced during this research was obtaining different data sets to perform other case studies. This difficulty is associated with public and private companies with information security contracts, preventing the availability of these data for the general public. Another limitation is the difficulty of providing a generic machine learning solution to work with other data sets associated with different contexts.

As future work, we want to test our visual analytics approach with different data sets. We also aim to validate the cancellation prediction. For this, we intend to create a comparative analysis between the probability indicated by the solution with the reality at each time period. This analysis will serve as input for possible improvements in the prediction algorithm. Another improvement is the development of new interactive visualizations to allow the analysis of the correlation of the cancellation probability with each variable, using, for example, a chord diagram [5]. It is also possible to explore service data and create interactive charts for team analysis in search of discoveries.

Finally, we can say that our visual analytics approach allows CRM teams to make a quick analysis of customer data, even if they are bulky, thus facilitating the creation of strategies to reduce the churn rate. Besides, the algorithms and visualizations used made it possible to answer the research questions presented at the beginning of Subsect. 3.3 and opened space for further research.

[8] https://github.com/p-karol/VA-to-Reduce-Churn.

5 Conclusion

The work carried out reinforced the importance of using visual analytics to analyze large volumes of data. It is often complex to keep track of these data due to its dynamism, and it is not easy to relate them because they are spread over several different data sources. It would be more difficult to analyze data with customer information without visual analytics, both for information technology professionals and for an audience considered laymen in the area, such as retention analysts.

Therefore, the main contribution of this work was the dashboards as the resources that improve the ability of visual perception concerning the professionals involved in the customer retention process. They allow the analysis and understanding of information to create strategies and make decisions assertive. Moreover, the central issue in the approach development was the probability of cancellation based on the collected variables, and this result needed to be reliable. Thus, one of its advantages was the excellent performance of the Random Forest data mining algorithm, which obtained an accuracy of 87%.

The use case demonstrates that the final result was gratifying considering that our visual analytics approach brought new skills to a team, allowing them to experience this with interesting analysis, which brings motivation and a roadmap for the evolution of the work to be developed in the future.

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