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Application of Machine Learning in Churn Prediction Contexts – A literature review

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ABSTRACT
Customer loyalty is a fundamental aspect in the life of any company. In today's times, when marketing is increasingly personalized and relational, it is crucial to ensure that consumers remain interested in the products and services offered by the company. Faced with the abandonment of products or services, a scenario commonly called *churn*, it is crucial to understand the reasons behind this phenomenon. To this end, companies use a wide variety of forecasting systems, which are increasingly more complex. Taking into account that Artificial Intelligence (AI) tools evolve rapidly, this article aims to understand which sectors of activity are most conducive to the application of *machine learning* in the context of customer *churn* forecasting. To meet this objective, a systematic literature review was adopted, taking into account the period 2020-2024. It is concluded that *machine learning*, applied in *churn* prediction models, is widely proposed by several authors throughout the analyzed period. Most of the studies resulting from this research focus on applications in the telecommunications sector, followed by the banking sector. It is also concluded that several methods are used in this context, but with special focus on *Random Forest (RF).*

Keywords: Churn, Machine Learning, Artificial Intelligence.

INTRODUCTION

Today's companies, faced with the rapid changes and uncertainties of the environment, and also to face the strong competition, multiply their efforts to ensure the permanence of their customers. They invest large amounts in sophisticated technological systems (CRM, Data-Base Marketing, Geomarketing, etc.) that allow them to know more deeply the consumption habits of their customers, so that they can meet their needs and thus ensure their loyalty.

When addressing the issue of customer retention, it is important to take into account the opinion of Kotler & Keller (2019). They suggest that it is more expensive to seek new customers than to retain current ones (KOTLER & KELLER, 2019, p. 150).

As loyalty is an essential aspect in a business context, it is also important to determine the respective *churn rate*.

CHURN

The term *churn* is used to define customer abandonment or abandonment. More specifically, a *churn* rate "corresponds to the percentage of customers lost in a specific period of time, not counting new

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customers acquired in that period." (SKIRTS *et al.*, 2018, p. 1). A high *churn* rate should lead the company to consider measures to understand the reasons for this abandonment.

In terms of classification, LAZAROV & CAPOTA (2007, p. 2) suggest the existence of three types of *churn*: active/deliberate, rotational/incidental and passive/non-voluntary.

The first set includes deliberate and conscious withdrawals by customers. They abandon the service for reasons related to, for example, dissatisfaction with products/services, poor customer service, complaints handled incorrectly, unjustified price increases, etc.

In the second set, the authors exemplify financial incapacity and also with the change of place of residence.

Finally, we have the withdrawal at the initiative of the company, perhaps because it feels that that customer no longer becomes profitable. Often, the amounts invested in retaining certain customers can be higher than the value of the purchases made by those same customers, so they translate into losses.

MACHINE LEARNING

Moving on to the technological component, and before addressing *machine learning* itself, it is important to start by understanding the concept of AI - Artificial Intelligence, whose origins date back to Alain Touring, in 1950. According to MAIA (2018, pp. 128-129), "(...) the text *Computing machinery and intelligence*, is currently considered an important milestone in the theory of computation, (...)".

According to GOMES (2010, p. 234), AI "(...) It covers a huge variety of subfields, from general-purpose areas such as learning and perception to specific tasks such as chess games, proof of mathematical theorems, creation of poetry, and diagnosis of disease."

In a business context, the applications of AI are beginning to be vast. According to GONÇALVES *et al.* (2023, p. 2), "In companies, artificial intelligence is used to boost results, increase productivity, and save time."

An increasingly common term in the AI environment is *machine learning*, which is understood as "(...) an area of AI whose objective is the development of computational techniques on learning, as well as the construction of systems capable of acquiring knowledge automatically." (MONARD & BARANAUSKAS, 2003, p. 39).

In the literature, we can find several studies that elucidate us in relation to this diversity of contexts: in the inflation forecast (FREITAS, 2019), in the demand forecast (DOS SANTOS, 2021), in the prediction of the evolution of investment funds (LINS, 2020), in the prediction of industrial processes (SOUSA, 2023), in the climate prediction (AGUIAR, 2022), in the prediction of internal soil erosion (ALBUQUERQUE & CAVALCANTE, 2022), among many others.

According to WANG *et al.* (2022, pp. 57-58), the most common types of models/techniques in *churn* prediction using *machine learning* are the following: *Decision Trees (DT´s), Random Forest (RF), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), Naive Bayes (NB), Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), Gradient Boosting Model (GBM)*. It should be noted that all these models have different degrees of complexity and can be applied individually or through integration with several other models.

In Decision Trees (*DT's*) "The algorithm starts by choosing the most general decision tree, containing only the initial node, called the root node. Based on this node, the algorithm works recursively on each child node, refining the tree until each subset belongs to a single class." (CARVALHO, 2014, p. 48).

As for Random *Forest (RF)*), it can be said that they are "(...) a co-learning method for classification and regression that operates by constructing multiple decision trees at the time of training and producing the class, which is the mode of the outputs generated by individual trees." (SANTOS, 2020, p. 29).

Logistic Regression (LR)), which "(...) It is a statistical technique that aims to model, based on a set of observations, the "logistic" relationship between a dichotomous response variable and a series of numerical (continuous, discrete) and/or categorical explanatory variables." (CABRAL, 2013, p. 15).

The Stochastic *Gradient Descent (SGD)* is used in situations that aim to minimize losses. For DA SILVA MELO (2022, p. 11) "(...) is an iterative method that aims to optimize an objective function by choosing a random instance of the training set at each step and calculating the gradient based on that single instance."

Support *Vector Machines (SVM)* are "(...) A classifier formally defined by a separation hyperplane. The goal of SVM is to find among all the hyperplanes the one that minimizes the empirical risk, that is, it seeks to maximize the margin of the linear classifier." (PEREIRA, 2018, p. 38).

The Naive Bayes classifier is understood to be "(...) a probabilistic model, being a particular case of Bayesian network with inference, where the number of parents in the network corresponds to a node (...)" (SIVIERO & JÚNIOR, 2011, p. 3).

In the *Multi-Layer Perceptron (MLP),* the source nodes form three layers: input layer, hidden layer, and output layer (SOUZA, 2012, p. 21).

As for *K-Nearest Neighbors (KNN),* as their name suggests, they are an algorithm that seeks to identify the neighbors that are closest to a certain point. In this context, the Euclidean distance and the Manhattan distance are frequently used (DOS REIS, 2012, p. 4).

Finally, the *Gradient Boosting Model (GBM)* Augmentation, "(...) consists of iteratively using weak estimators to make estimates and then adding this weighted estimate to an estimate generated by a strong estimator." (SPOLADOR, 2021, p. 24). In this context, WANG *et al*. (2022, p. 58) talk about *XGBoost* and *LightGBM*.

Taking these considerations into account, in this study we will seek to understand in which sectors machine learning is applied in the context of *churn forecasting*.

OBJECTIVE

The main objective of this study is to understand which sectors of activity are most conducive to the application of *machine learning* in the context of customer *churn* forecasting. Subsequently, for the selected studies, we tried to understand the frequency with which the methods evidenced by WANG *et al. are used.* (2022, pp. 57-58).

METHODOLOGY

To achieve the main objective of this study, a systematic literature review (SLR) methodology was followed using the well-known Scopus database. In view of the large number of studies that are available today, a systematic review of the literature is an appropriate method for this research.

In the scope of this article, the steps defined by TRANFIELD *et al.* (2003) in studies of this nature: the planning, review and dissemination/dissemination of the results obtained.

On February 4, 2024, the actual research process began. The first search, using the expression *churn prediction machine learning sector* and without resorting to the use of any refinement, led to 128 results. Subsequently, the results were calculated on the basis of a first refinement, i.e. taking into account a time period from 2020 to 2024, and 106 documents were obtained. In a second refinement, the search was limited to the keywords "Machine learning" and "Customer Churn Prediction", which led to 73 results, which were exported to the Zotero platform.

Then, the titles and abstracts of the 73 studies were read, and 43 were selected. In some cases, it was also necessary to read the results and conclusions of certain studies to understand what methods were used/suggested by the authors.

We discarded 30 studies that analysed the topic in a generic way, not focusing on any particular sector, that analysed *machine learning* methods in general, state of the art, systematic literature reviews, questionnaire-based studies, studies focusing on more than one sector simultaneously, studies applied from different perspectives of customers/consumers (e.g. students, collaborators), specific *deep learning* studies, and paywalled studies.

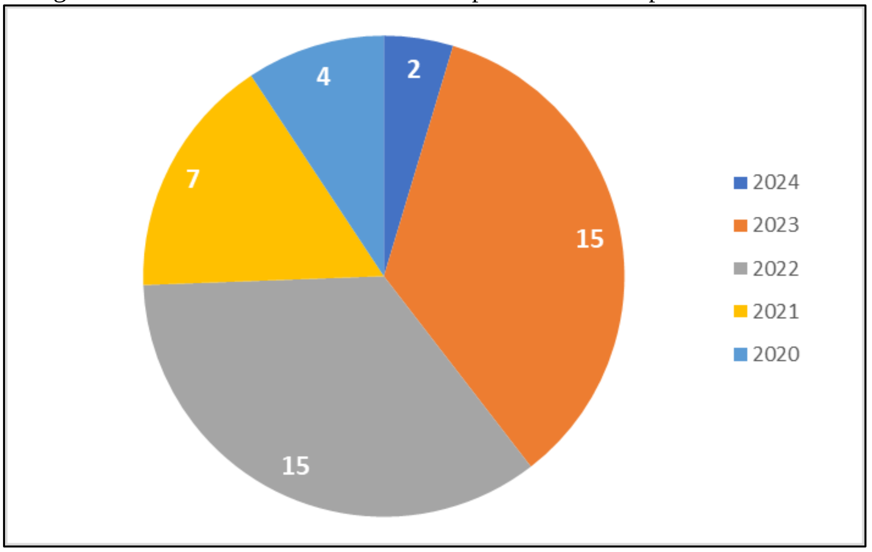
RESULTS

From the point of view of scientific production in annual terms, Figure 1, there is an upward trend. In 2021 we found only 7 studies. The following years, 2022 (15) and 2023 (15), saw a clear growth in the number of publications, mainly in Banking and Telecommunications.

It should also be noted that it was in 2022 that the only study of this period related to Factoring was published (paper in conference by BOZKAN (2022, May)), and in 2023 the only study related to Renting (article by SUH (2023)), which leads to the conclusion that this tool has only recently been looked at within the scope of these two sectors of activity.

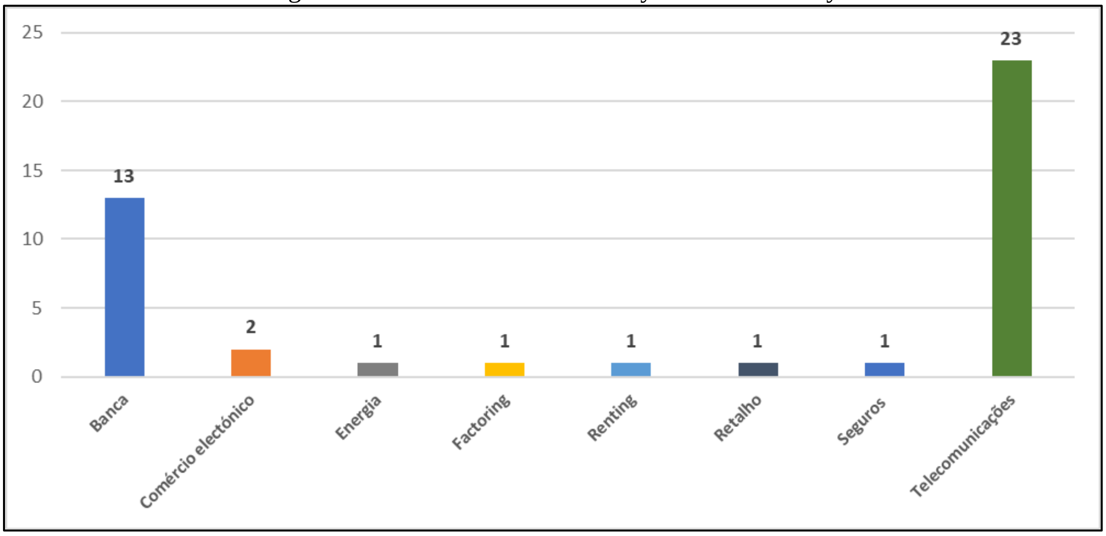
When analysing the current year 2024, so far, it can be seen that two studies of this nature have already been published, both of which concern the telecommunications sector. It is the only sector that has already obtained publications this year, and taking into account that it stood out in the period under review, it can be said that the trend is one of continuity.

Figure 1 – Annual distribution of studies published in the period 2020-2024



In the recent period, 2020-2024, machine learning is applied in various sectors of activity. Telecommunications is the sector with the largest number of studies, a total of 23. It is followed by Banca with 13 studies. In third place we have E-commerce, with 2 studies. Finally, with only one study each, we have the remaining sectors: Energy, Factoring, Renting, Retail and Insurance (Figure 2).

Figure 2 – Distribution of studies by sector of activity



See the summary of studies for each of the eight sectors identified in Table 2.

Table 2 – List of studies on *machine learning* in various sectors

Sector	Studies
Newsstand	Sony & AMP; Nelson (2023); DNNMEJ (2023, September); Murindon *E. T. al.*(2023, April); Beauty *ET, Al.*(2023, April); Tran *ET, Al.*(2023); De Lima Lemos, *E. T. al.*(2022); N.V . *ET, Al.*(2022, November); Agarwal, *ET, Al.*(2022, October); Haddadi (2022, May); Elyusofi & AMP; Mo'Hamed (2022); Bhujbal & AMP; in Bavdan (2021, November); Sagala & Parmai (2021, October); Rahman & Kumar (2020, November)
Electronic Trade	Nagaraj *et al.* (2023, January); Gopal & MohdNawi (2021, December)
Energy	Vezzoli *et al.* (2020)
Factoring	Bozkan (2022, May)
Renting	Suh (2023)
Retail	Abbas (2022, December)
Insurance	Das & Gondkar (2021)
Telecommunications	Wag *E. T. al.*(2024); Moradi *E.T. al.*(2024); Imani & Urbania (2023); Booklina *E.T. al.*(2023); Shahid *E.T. al.*(2023, February); Navienkumar & Lalithamani (2023, Julie); Lim *ET, Al.*(2023, August); Mahajan & Arif (2023, September); Raj & Vetuthanam (2023, April); Srinivasan *ET Al.*(2023, January); Al-Shourbazi (2022); Zdanavičiūtė *ET Al.*(2022); Shrestha & Shakya (2022); Salian (2022, December); Prakash *E. T. al.*(2022, December); Faritha Banu (2022); Mirza *E.T. al.*(2022); Vakil *ET al.*(2022, January); Liu *et al.* (2022); Karamollaoğlu *et al.* (2021, September); Saheed & Hambali (2021, October); Shumaly *et al.* (2020, October); Abou el Kassem *et al.* (2020)

Source: Prepared by the authors based on a search in the Scopus database on 04 Feb. 2024

Turning now to some considerations in relation to the frequency of use of different methods in the context of telecommunications and banking, the sectors that have clearly stood out with the largest number of studies, it has been noted that numerous methods have been applied, used individually or in an integrated way.

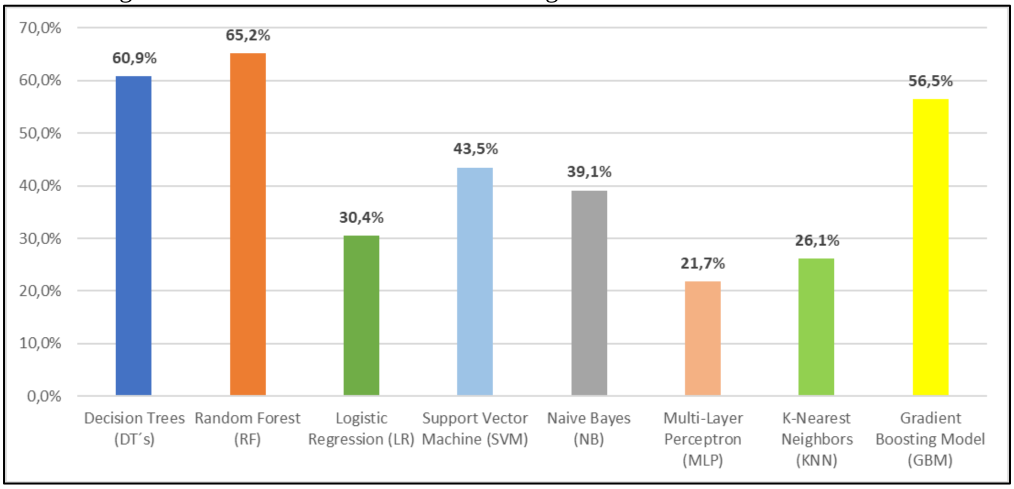
It is important to note that, in addition to the methods mentioned above, sometimes others are used and even some innovative ones are proposed. However, in this article, we only stick to the methods considered by WANG *et al.* (2022, pp. 57-58), which we have seen above. It is customary, within the scope of the studies found, to compare the performance in relation to several algorithms.

It should be noted that no studies were found that addressed *Stochastic Gradient Descent (SGD).* On the other hand, algorithms such as *XGBoost*, *CatBoost*, among others were considered derivatives of GBM.

In the context of Telecommunications, with the largest number of studies, 23, the *Random Forest* (65.2%) and *the Decisions Trees* (60.9%) are the ones that stand out. This is followed by *Gradient Boosting Models* (56.5%), *Support Vector Machine* (43.5%), *Naive Bayes* (39.1%) and *Logistic Regression* (30.4%).

In the set of *Gradient Boosting Models* we found references to *XGBoost*, *LightGBM*, *AdaBoost* and also *CatBoost*.

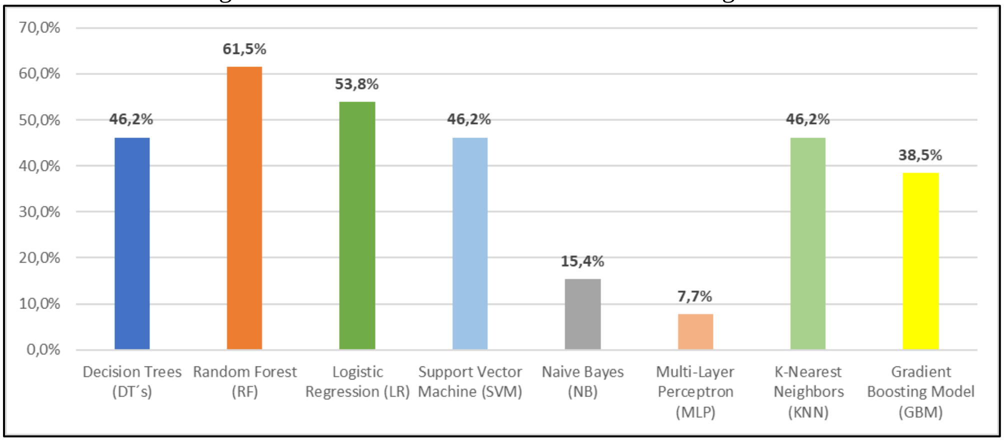
Figure 3 – Methods used in studies relating to the telecommunications sector



On the other hand, the most used methods in the 13 studies on the banking sector, Figure 4, are *the Random Forest* (61.5%) and *the Logistic Regression* (53.8%). With the same value, 46.2%, we have Decision *Trees*, Suport Vector Machines and K-Nearest Neighbors.

In the Gradient Boosting Models (38.5%) there were also visible references to XGBoost, LightGBM, AdaBoost and CatBoost tools.

Figure 4 – Methods used in studies on the banking sector



FINAL THOUGHTS

This article aimed to evaluate the use of *machine learning* in the prediction of *churn*, the rate of customer abandonment. It was concluded that, in the period 2020-2024, there are many proposals for models in various sectors. The telecommunications sector stands out, with 23 studies. The panel took second place in the ranking with 13 studies.

It was also possible to notice that the methods used in these studies are quite varied: *Decision Trees (DT's), Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Naive Bayes (NB), Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), Gradient Boosting Model (GBM).*

Random Forest (RF) was the method that obtained the most significant values both in the context of telecommunications and in the context of banking.

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