Prediction customer dropout using machine learning

Current situation

Pedro Sobreiro, Javier Berrocal (Thesis Supervisor), José Garcia Alonso (Co-supervisor),

University of Extremadura *pdealexa@alumnos.unex.es*

Webinar, 11 September 2020

Summary

Research goals

This thesis focuses in applying machine learning techniques aiming to find answers to the following questions:

- Q1: Which are the patterns related to dropout?
- Q2: There are temporal patterns related to the dropout?
- Q3: Is possible to increase customer lifetime value employing machine learning techniques?

These questions are supported in a Systematic Literature Review, establishing the state of the art in this research area. Our aim is to identify information that can be employed to increase their Customer Lifetime Value, which allows us to develop insights to support retention systems to reduce dropout in customers in a contractual setting.

Research plan

1. Developing the systematic literature review supporting the thesis: "Dropout Prediction: A Systematic Literature Review" (in progress)
2. Exploring existing machine learning techniques to predict dropout (in progress)
3. Creation of an ensemble method to improve dropout prediction accuracy
4. Developing article addressing an ensemble method using a case study
5. Finishing and thesis delivery

Research plan

Name
Developing the systematic literature review supporting the thesis
Exploring existing machine learning approaches to predict dropout
Creation of an ensemble method to increase dropout prediction accuracy
Developing article addressing an ensemble method
Finishing and thesis delivery

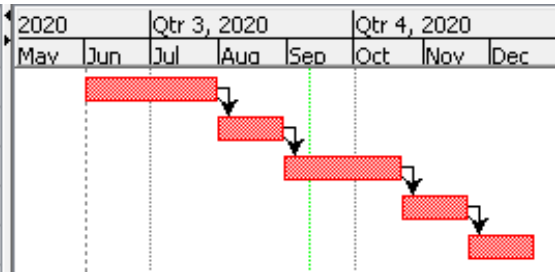


Figure: Activities timeline

Introduction

Some background...

- Customer analysis is fundamental to develop business and marketing intelligence (Sheth, Mittal, & Newman, 1998), supporting the understanding of historical data identifying trends and patterns (Berry & Linoff, 2004);
- This process is also known as data mining, the extraction of knowledge from data (Han & Kamber, 2006);
- According to Han, Kamber, and Pei (2012), these tasks present many similarities between data mining and machine learning;

Sheth, J. N., Mittal, B., & Newman, B. (1998). Customer Behavior: Consumer Behavior and Beyond (1 edition). Fort Worth, TX: South-Western College Pub.

Berry, M. J. A., & Linoff, G. (2004). Data mining techniques: For marketing, sales, and customer relationship management (2nd ed). Indianapolis, Ind: Wiley Pub.

Han, J., & Kamber, M. (2006). Data mining: Concepts and techniques (2nd ed). Amsterdam; Boston: San Francisco, CA: Elsevier; Morgan Kaufmann.

Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and techniques (3. ed). Amsterdam: Elsevier; Morgan Kaufmann.

Introduction

Some background...

- Machine learning could be used to extract knowledge to understand dropout for the development of effective retention strategies (Verbeke, Martens, Mues, & Baesens, 2011);
- Machine learning algorithms have been used to predict customer dropout (Bandara, Perera, & Alahakoon, 2013), without however to consider the timings of the dropout;
- Machine learning can be used to develop of customer retention strategies based on existing data (Verbeke et al., 2011), extracting patterns from data (Kelleher et al., 2015), that support the development of counteractions before an event occurs.

Verbeke, W., Martens, D., Mues, C., & Baesens, B. (2011). Building comprehensible customer churn prediction models with advanced rule induction techniques. Expert Systems with Applications, 38(3), 2354–2364. doi: 10.1016/j.eswa.2010.08.023

Bandara, W. M. C., Perera, A. S., & Alahakoon, D. (2013). Churn prediction methodologies in the telecommunications sector: A survey. 2013 International Conference on Advances in ICT for Emerging Regions (ICTer), 172–176. doi: 10/ggtgjg

Verbeke, W., Martens, D., Mues, C., & Baesens, B. (2011). Building comprehensible customer churn prediction models with advanced rule induction techniques. Expert Systems with Applications, 38(3), 2354–2364. doi: 10.1016/j.eswa.2010.08.023

Introduction

Some background...

- The identification of the dropout can be developed in different contexts: customers that buy in contractual settings and non-contractual settings where a firm have to infer if the customer is still active (Gupta et al. ,2006) ;
- The main characteristic of a contractual setting is a contact of the customer canceling a subscription (Fader & Hardie, 2007);
- Customer dropout prediction should consider the context, where there is a contractual or non-contractual setting.

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., ... Sriram, S. (2006). Modeling Customer Lifetime Value. Journal of Service Research, 9(2), 139–155. doi: 10.1177/1094670506293810

Fader, P. S., & Hardie, B. G. S. (2007). How to project customer retention. Journal of Interactive Marketing, 21(1), 76–90. doi: 10.1002/dir.20074

Introduction

Summary

- It is also know, that the costs of retaining customers are lower when compared to the costs of attracting new ones (Edward & Sahadev, 2011), reinforced by that the reduction of the dropout rates could represent an increase in the profits (Reichheld, 1996);
- Machine learning algorithms have been used to predict customer dropout (Bandara, Perera, & Alahakoon, 2013);
- But, to our knowledge, there is a lack of an overview of research related to the use of machine learning techniques to target customer dropout with contractual settings considering also the timings of the dropout.

Edward, M., & Sahadev, S. (2011). Role of switching costs in the service quality, perceived value, customer satisfaction and customer retention linkage. Asia Pacific Journal of Marketing and Logistics, 23(3), 327–345. doi: 10.1108/13555851111143240

Reichheld, F. F. (1996, Março 1). Learning from Customer Defections. Harvard Business Review, (March–April 1996). Retrieved from https://hbr.org/1996/03/learning-from-customer-defections

Bandara, W. M. C., Perera, A. S., & Alahakoon, D. (2013). Churn prediction methodologies in the telecommunications sector: A survey. 2013 International Conference on Advances in ICT for Emerging Regions (ICTer), 172–176. doi: 10/ggtgjg

Research gap

Considering this context, this research tries to analyze the state of the art to identify Machine Learning studies to predict customer dropout to support the development of counteractions before the customer churns, considering also when it occurs.

Methodology

- Was developed a Systematic Literature Review (SLR) in three stages (Kitchenham & Charters, 2007): Plan, Conduct and Report;
- Plan: definition of the research need, identification of the research questions and the development of the review protocol;
- Conduct: research identification, study selections, quality assessment, data extraction, finishing with the data synthesis;
- Report: stage that develops the activity report review.

Kitchenham, B., & Charters, S. (2007). Guidelines for performing structural literature reviews in software engineering (pp. 1–26) [Joint technical report]. Australia: Keele Univ., and Empirical Software Eng., Nat'l ICT.

Systematic Literature Review Phases

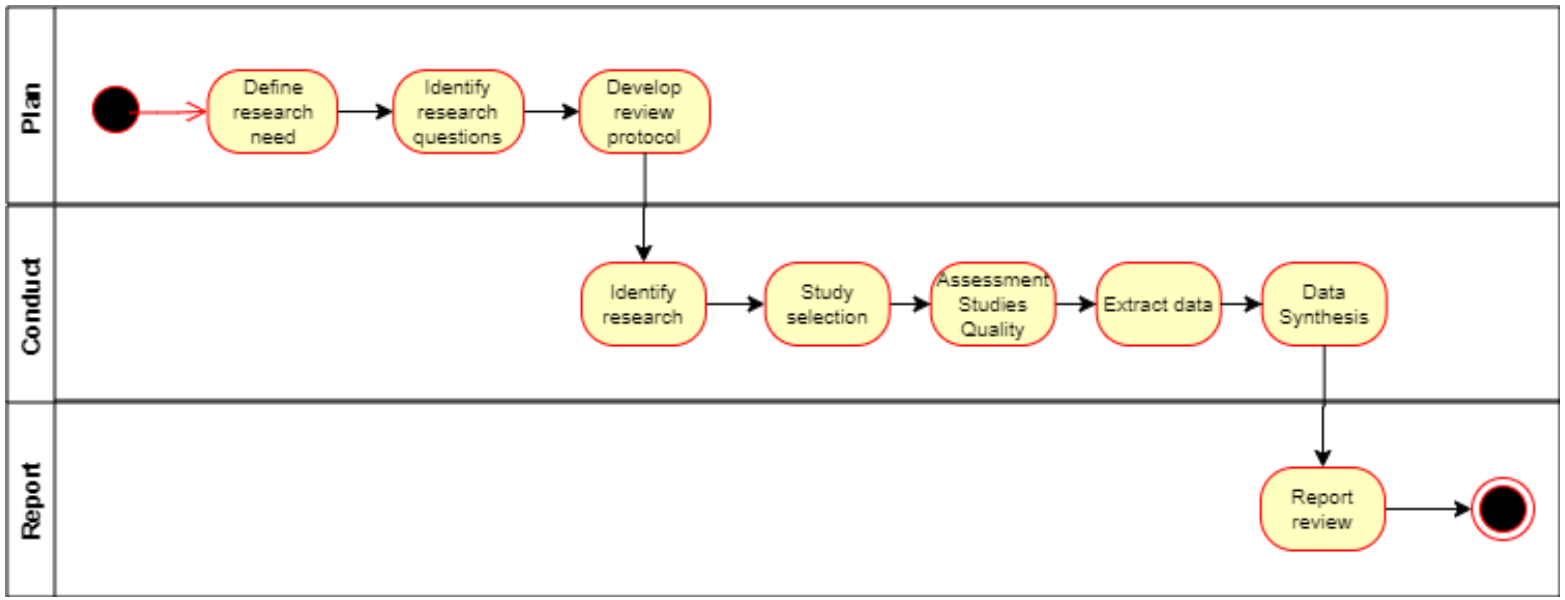


Figure: SLR phases based on Kitchenham and Charter (2007)

Research questions

What is the current state of machine learning research in existing studies to predict dropout in contractual settings? Based in this question were identified the following questions:

- RQ1: What studies have been published?;
- RQ2: Which algorithms have been used to predict the dropout? This question will also address algorithms used by business area (as suggested in activity 6)
- RQ3: What are the more relevant features related to predicting customer dropout?
- RQ4: When the dropout occurs?
- RQ5: What is the accuracy of the machine learning algorithms to predict dropout?

Population, Intervention, Comparison, Outcomes and Context

Table: PICOC criteria

PICOC	Description
Population	Research papers about dropout with contractual settings
Intervention	Machine learning algorithms to predict dropout
Comparison	Studies addressing machine learning algorithms to predict dropout
Outcome	Synthesis identifying research questions, gaps in the research domain and also best practices identified
Context	Academia and industry

Note: Context (PICOC) as suggested Kitchenham and Charters (2007) and proposed by Petticrew and Roberts (Petticrew & Roberts, 2006) to support the development of the search string.

Kitchenham, B., & Charters, S. (2007). Guidelines for performing structural literature reviews in software engineering (pp. 1–26) [Joint technical report]. Australia: Keele Univ., and Empirical Software Eng., Nat l ICT.

Petticrew, M., & Roberts, H. (2006). Systematic reviews in the social sciences: A practical guide. Malden, MA ; Oxford: Blackwell Pub.

Search

- Search string: ((“customer dropout”) OR (“customer churn”) AND “machine learning” AND (“contractual” OR “membership”));
- Applied to the title, abstract, and keywords in the search period between January 2000 and June 2020
- The exclusion criteria were Books, Non-English articles, patents, and thesis
- Sources SpringerLink, Scopus, Science@Direct, ISI Web of Science, IEEE Digital Library, and ACM Digital Library
- The selection process was developed using ASReview (ASReview Core Development Team, 2019) creating a dataset of the identified articles, providing five relevant papers and five irrelevant papers to train Machine Learning model Naïve Bayes;

Kitchenham, B., & Charters, S. (2007). Guidelines for performing structural literature reviews in software engineering (pp. 1–26) [Joint technical report]. Australia: Keele Univ., and Empirical Software Eng., Nat l ICT.

Petticrew, M., & Roberts, H. (2006). Systematic reviews in the social sciences: A practical guide. Malden, MA ; Oxford: Blackwell Pub.

Results

- 449 studies were found: Scopus 210; IEEE 20; SpringerLink 79; Science Direct 126; ISI Web of Knowledge 6 and ACM 8) in the first step of the conduct (Identify research);
- 20 incomplete items were removed
- 16 duplicates were removed
- 335 were removed after ASReview
- 78 papers selected
- Data analysis procedure available here.

RQ1. What studies have been published?

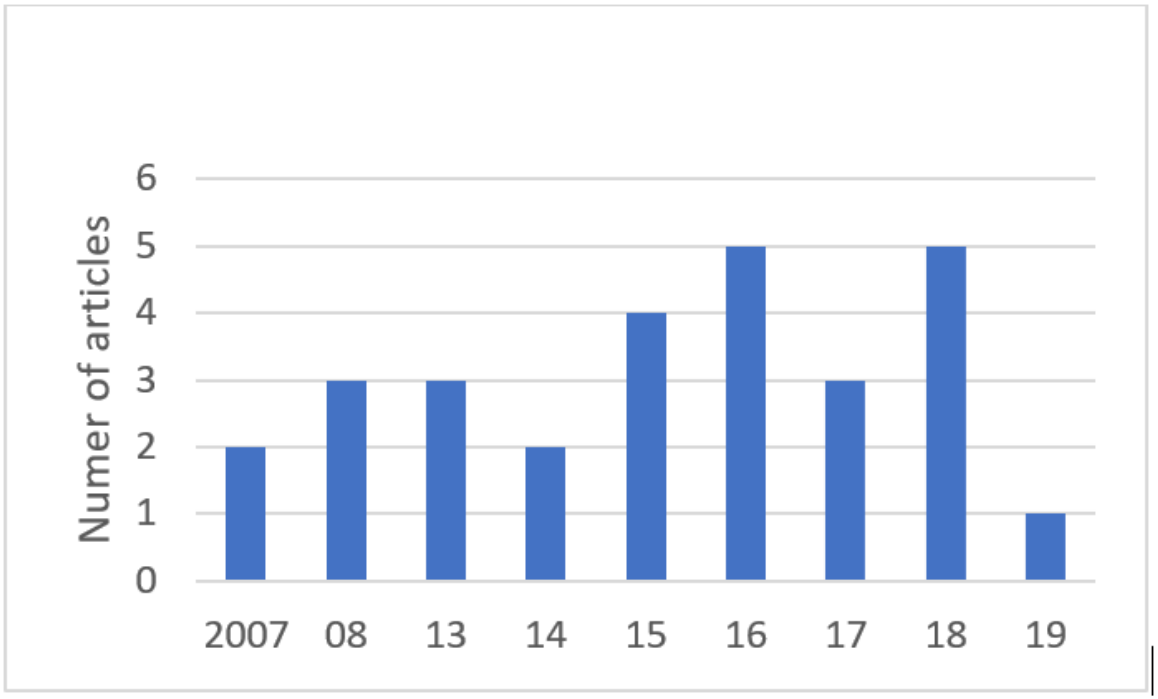


Figure: Articles per year after quality assessment

RQ1. What studies have been published?

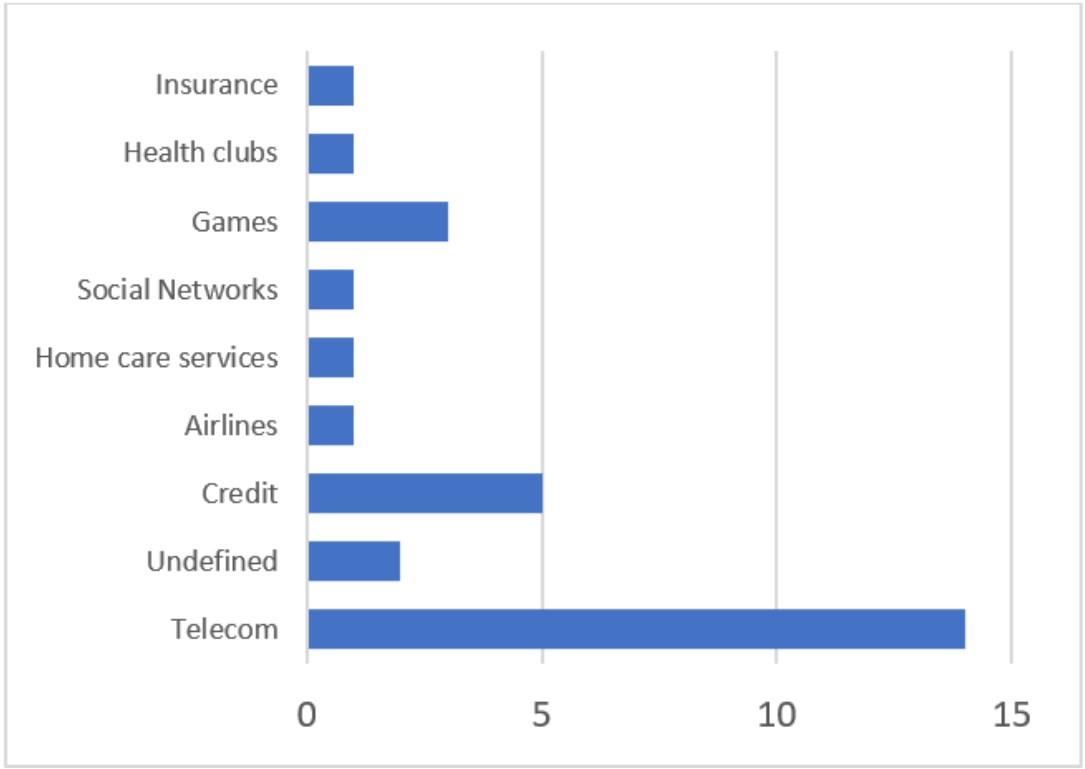
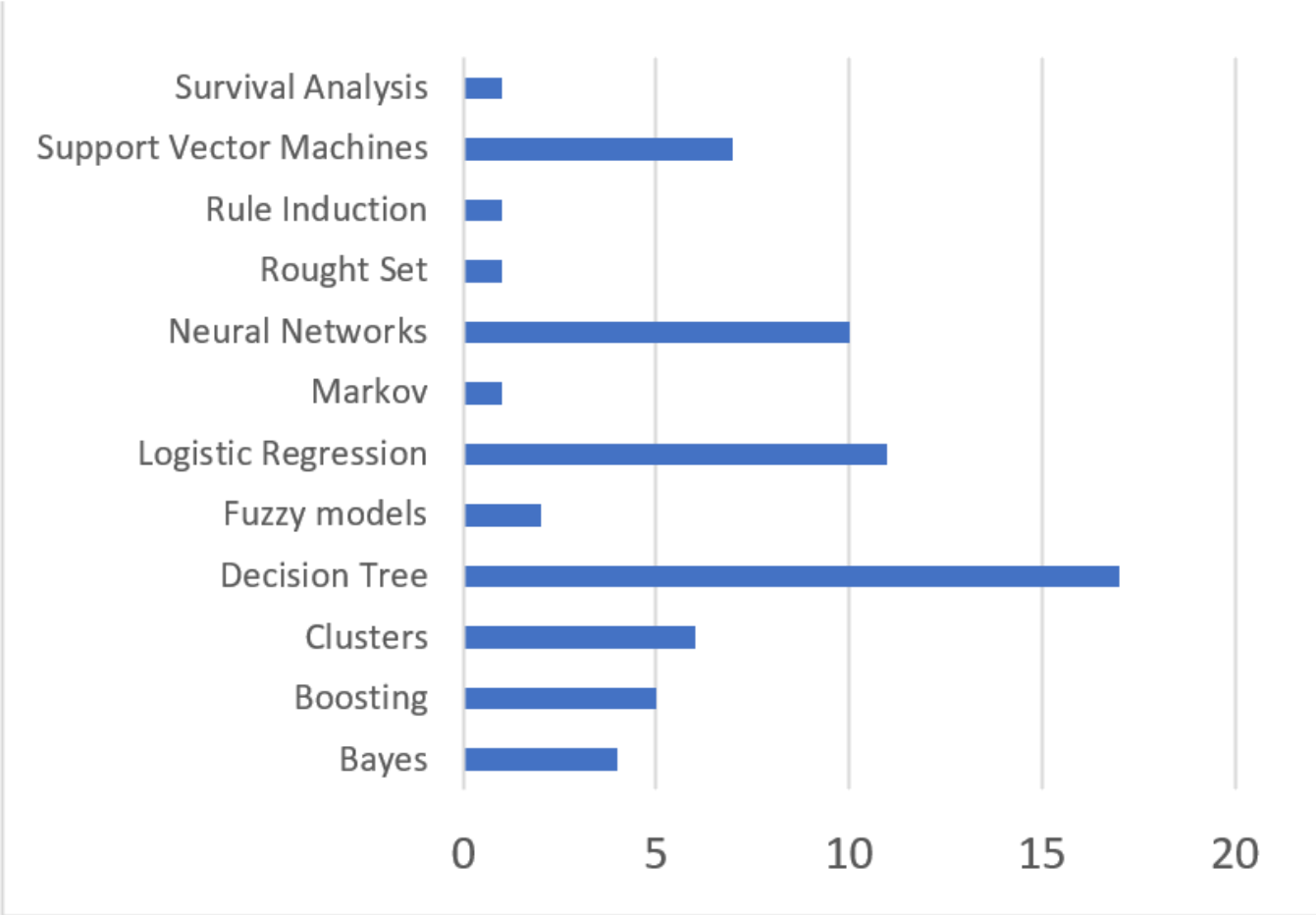


Figure: The number of studies per business context

RQ2: Which algorithms have been used to predict the dropout?



RQ3: What are the more relevant features related to predicting customer dropout?

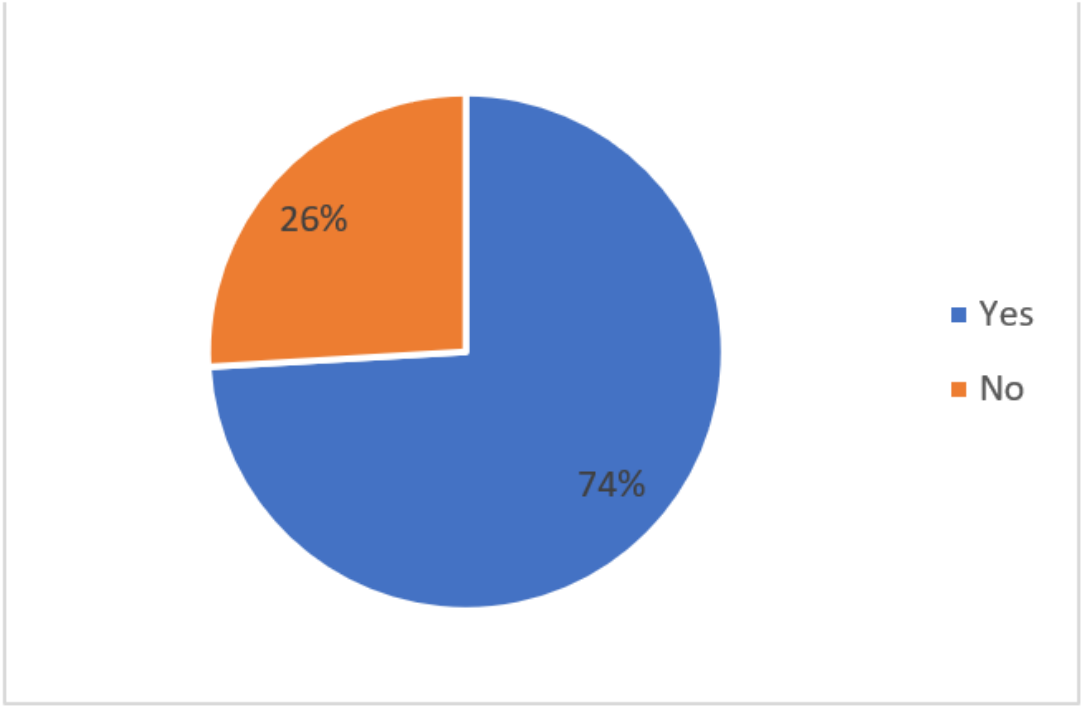


Figure: Percentage of studies identifying the relevant features

RQ4: When the dropout occurs?

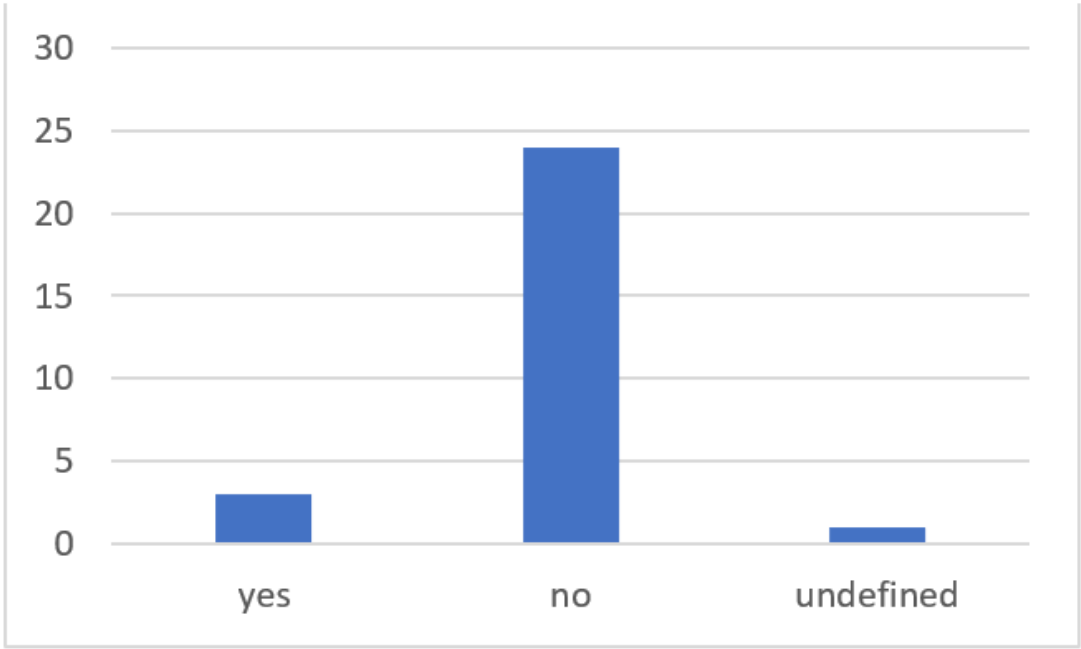


Figure: The number of studies addressing the dropout timings

RQ5: What is the accuracy of the machine learning algorithms to predict dropout?

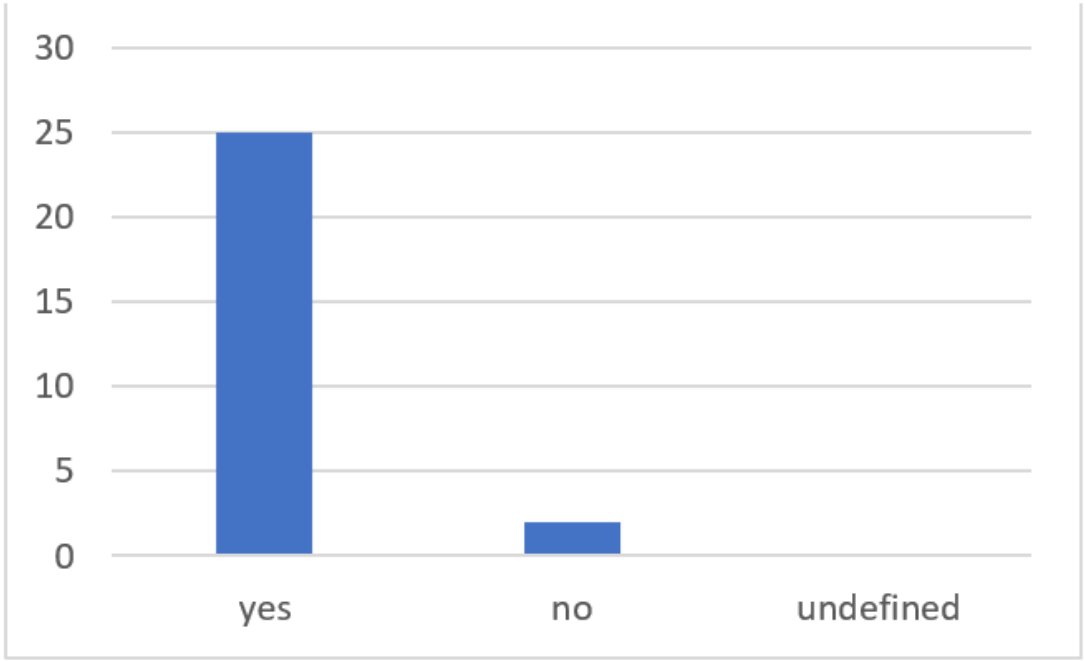


Figure: Number of studies identifying the prediction accuracy

Exploring existing machine learning techniques

- Was tested class train/test stratification in the target variable, imbalance datasets, grid search optimization targeting AUC for classification (dropout,non-dropout)
- The class imbalance aproaches to adjust the weights inversely proportional to class frequencies in the input data using the library scikit-learn (Pedregosa et al., 2011).
- Hyperparameters optimisation developed using grid search targeting AUC as the optimization goal considering the discriminatory power (Emeterio et al., 2016).
- Logistic Regression (LR), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Gradient Boosting Classifier (GBC) best performances in GBC (accuracy, sensitivity, precision, F1 Score) and RFC in AUC.
- Code book, dataset and Jupyter notebook code

Exploring existing machine learning techniques

1732 *Journal of Reviews on Global Economics*, 2019, *8*, 1732-1740

Predicting High-Value Customers in a Portuguese Wine Company

Pedro Sobreiro[1], Domingos Martinho[2,*], António Pratas[2], Jose Garcia-Alonso[3] and Javier Berrocal[3]

[1]*Escola Superior de Desporto de Rio Maior, Instituto Politécnico de Santarém, Portugal*

[2]*ISLA Santarém, Portugal*

[3]*Quercus Software Engineering Group, University of Extremadura, Spain*

Abstract: Wine companies operate in a very competitive environment in which they must provide better-customised services and products to survive and gain advantage. The high customer turnover rate is a problem for these companies. This work aims to provide wine companies with new knowledge about customers that help to retain the existing ones. The study applies a collected dataset from a transaction database in a medium-sized Portuguese wine company to determinate: (1) customer lifetime value; (2) cluster customer value as output (customer loyalty). The measurement of the customer lifetime value (CLV) was analysed using the Pareto/NBD model and gamma-gamma model. Clustering techniques are employed to segment customers according to Recency, Frequency, and Monetary (RFM) values. Study findings show that exists three clusters with different interest to the marketing strategies, identifying the high-value customers, to target using marketing to increase their lifetime value effectively. The implications for the marketing strategy decisions is that using techniques based on the RFM model can make the most from data of customers and transactions databases and thus create sustainable advantages.

Keywords: Customer lifetime value, clustering, wine marketing, RFM model.

Figure: Publication using an technique for Q3 "Is possible to increase customer lifetime value employing machine learning techniques?"

Conclusion

- The telecommunications sector is the area where are being developed most of the studies, which identifies some research areas gaps that need to be addressed;
- Algorithms to predict dropout using also survival analysis approaches is an area under researched, only three research papers, however considering the number of citations these approaches getting the attention (Perianez et al., 2016);
- The use of algorithms to explore the timings when the dropout will occur is an approach that could complement the dropout prediction, supporting the development of actions considering both the probability and when should be developed countermeasures to avoid the customer dropout

Perianez, A., Saas, A., Guitart, A., & Magne, C. (2016). Churn Prediction in Mobile Social Games: Towards a Complete Assessment Using Survival Ensembles. 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA), 564–573. doi: 10/ggtgjh

Thanks!

Start where you are. Use what you have. Do what you can. **Arthur Ashe**