

Development of credit scores with telco data using Machine Learning and agile methodology in Brazil

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ABSTRACT

The mobile phones market in Brazil is one of the largest in the world and this huge volume is concentrated in prepaid lines. This distribution reflects the population composed of lower income, lower credit profile and lower bankarization. However, in recent years the prepaid market has been falling, while the postpaid market has grown rapidly, due to the increase in the customer usage of data. This scenario makes selecting customers for upgrade a key point in the strategy of telecommunications companies in Brazil.

In this context, Claro Brazil decided to invest more analytical intelligence in credit check for upgrades, which used to consider exclusively external credit score bureau verification during the sale process. Thus, the challenge is to select costumers for postpaid by considering the future propensity pay, optimizing sales channel campaigns, which can lead to increased conversions, improved payment performance and reducing costs with credit bureaus.

For this challenge, an analytics squad was started that worked using agile methodology. With machine learning techniques and through prepaid customer data, such as top up history, data usage, voice usage, regions, etc., a high accuracy credit score was obtained, without dependence on the bureau's score and a pre-qualification customers' for the upgrade started to be made. With this solution, the first payment default reduced 31% and the sales increased 11%, beyond the internal results, this predictive model combined with other behaviors models, made it possible to launch the Claro Score to the market, as a new data monetization product, helping companies to improve results and enabling people to improve their lives.

INTRODUCTION

In Brazil 30% of the Brazilian population is outside the financial system, in addition, 41.1% of the people are in the informal labor market. This profile makes a large portion of the population less known by the credit bureaus and traditional models of credit assessment have difficulty in assigning credit scores to these people. This limitation of information leads this people to not access credit lines or to the consumption of recurring services.

This public, due to its financial characteristics, is typically a prepaid mobile phone customer. In Brazil we have very high penetration of mobile telephony and people are increasingly connected, generating a huge amount of data that allows us to deepen our knowledge about them.

The difficulty in qualifying these customers directly impacts the result of prepaid to postpaid upgrades, reducing qualified audiences and leading to higher default rates. In addition, in the last few years the prepaid phone market has been falling, while the postpaid market has been increasing, making the upgrade actions a key part of the telecommunications companies' strategy.

In this scenario, Claro Brasil saw the possibility of developing a credit score based on internal data that was able to classify all audiences, regardless of professional activity or banking. In this way, taking advantage of the potential of data available in telecommunications operators combined with advanced prediction techniques.

THE EXTERNAL CONTEXT

CREDIT IN BRAZIL

In Brazil, traditional credit assessment models consider negative information from people, that is, they focus on information about defaults. This negative record is managed by some large credit bureaus that receive notifications of unpaid overdue debts from companies and consumers, from this information credit scores are generated that are consumed by practically all companies that grant some type of credit sale, loans or continuing services. This evaluation model generates great distortions in audiences that make up the "thin files", that is, audiences with little or no information in the credit bureaus.

As of mid-2019, this scenario tends to change, with the entry into force of law of the positive registration law, which ensures that payment (or positive) information is also shared with credit bureaus. However, in countries like Brazil, where there is a high level of economic informality, with large volumes of people with no account in banks and low income, automated credit assessment will always be more difficult, as there will always be little information from some strata. Without a more complete view of income, consumption habits and payment history, estimates of the ability to make new financial commitments will always be less accurate.

According to a 2018 World Bank survey carried out in 150 countries, 30% of the Brazilian population is outside the financial system, that is, they are people who do not use banking products on a daily basis. In addition, the survey shows that only 15% of people over 15 years old have a credit card. This characteristic leads to a vicious cycle, as people without information will find it more difficult to have access to banking services and because they do not have banking services, they will always have less information, always leaving the margin of the banking system and many consumer markets.

Along with the non-bankers, in 2019 Brazil presented a result of 41.1% of people in the informal labor market according to the IBGE National Household Sample Survey. They are people who work for themselves without forming a company or people who work for companies without formal ties. This group focuses on street vendors, day laborers, and activities that have recently emerged with the digitization of services, such as drivers or apps deliverers.

These combined profiles lead to a number of 48.4 million people in Thin Files in Brazil, according to SERASA Experian, that is, a contingent equivalent to Germany's economically active population, without enough information to consolidate a more accurate Score, which creates great difficulty in accessing credit and consumption, which are key to the economy, since it also allows its holders to open or expand businesses.

The level of household indebtedness in Brazil is 55% of annual income, according to OECD data. This level of indebtedness is low, when compared internationally. The sample average of 28 OECD countries for debt, which is 130% of annual income; indebtedness in Brazil is

much lower than other countries, even if compared only to other emerging countries, that is, there is a high potential for granting credit.

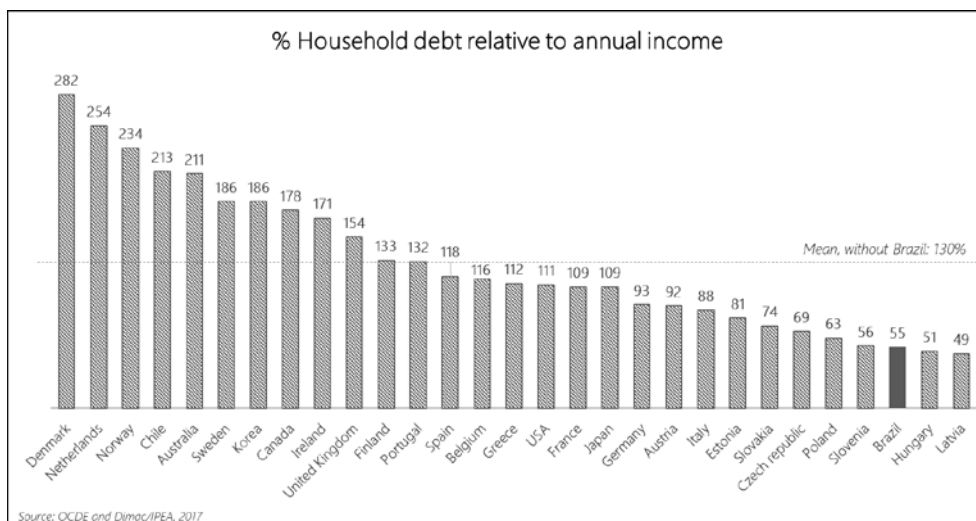


Figure 1. % Household indebtedness relative to annual income, 2017.

Although the level of indebtedness allows for greater expansion of credit taken by families, the high commitment of income to debt service is an important limiter. The cost of debt in Brazil is very high (interest and bank spread) and one of the factors that raises this level is the high default rate in the country. The percentage of defaults in Brazil is the highest in a sample of emerging and developed countries and, undoubtedly, one of the highest in the world.

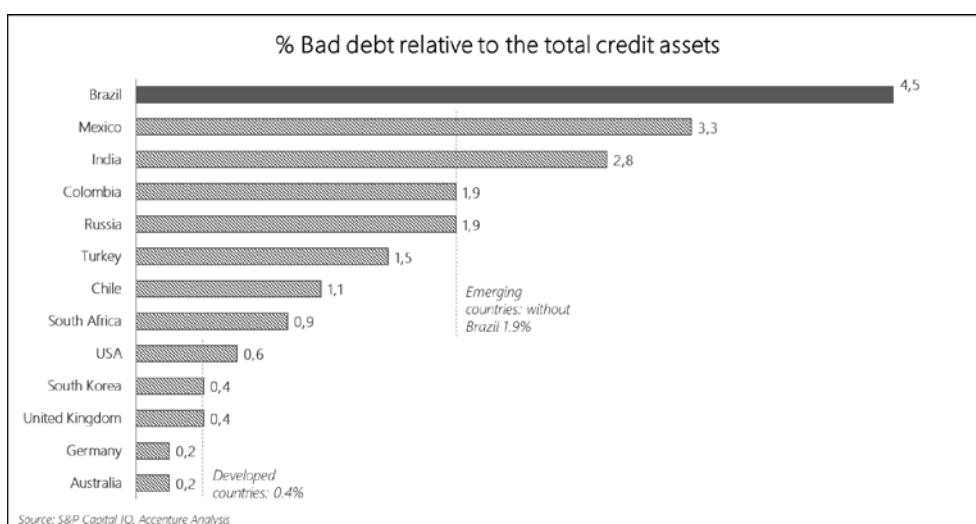


Figure 2. % Bad debt relative to the total credit assets, 2017.

Another important point regarding credit in Brazil is the low use of guarantees. Mainly due to bureaucratic processes, the recovery time of assets in guarantees is very long and the percentage of recovery is low, which makes this an alternative less adopted than in other countries. It leads to less mortgage loans and makes it difficult to grant loans to companies, because their assets are less considered.

We arrived at the following situation: companies grant little credit in Brazil and, despite having a low level of indebtedness in relation to income, we have a high default rate. In this scenario, increasing credit granting to stimulate the economy would lead to a significant increase in defaults, so companies avoid increasing aggressiveness in granting, so as not to make business unfeasible.

It is clear that improving credit assessment in Brazil would have a direct effect on greater credit approval for thin file customers, with controlled risk, as more people would have information available. As a result, sales or concession results increase and profitability increases.

The challenge is: How to do this in a country with so many people without information available? The answer may be in non-traditional credit assessment alternatives, such as telecommunications data.

As mobile phone penetrations in Brazil are around 97% and as the informal market is increasingly associated with digital services, audiences that have little information on traditional credit bureaus, leave a very rich trail of data on mobile operators. These data allow these companies to know their customers, even on prepaid ones, more than traditional credit score players and make it possible for the population that make up the thin file to have a richer credit rating.

BRAZIL CONNECTED BY TELECOMMUNICATIONS

The mobile phone market in Brazil is one of the largest in the world and, despite having a large low-income population; the number of mobile lines in the country is greater than the economically active population. This huge volume of lines is mainly concentrated in prepaid lines. The penetration of mobile telephony in the population is around 97%, the penetration of social networks is 66%, the penetration of fixed internet is 71% and the use of digital services through Apps has been growing rapidly, including as a source of income for many Brazilians.

In the last few years the market for prepaid lines has been falling, while the market for postpaid lines has been growing at an accelerated rate. The greater usage by customers pulls this migration. Now the people have more frequency and volume of data consumption, so the postpaid service has become more interesting.

The migration from prepaid to postpaid customers guarantees a higher and more stable average revenue per customer over the months, lower churn and provides more services to the customer. This migration is done mainly through active campaigns, via telephone contact or via text messages and these actions come from a pre-selection of the public, according to the internal premises.

The prepaid market, despite having a huge potential for revenues for telecommunications, is composed of higher concentrations of customers with lower income, lower credit profile and less bank accounts. This scenario makes the correct selection of clients for migration a key point in the strategy of telecommunications companies, as this public, due to its characteristics, typically has less traditional credit information.

The selection of customers for upgrade is usually made through credit policies based on scores contracted from external bureaus that aim to keep default and profitability at

acceptable levels. These scores are expensive and, for audiences with no history of financial transactions in the market, they may have had an insufficient result.

In this context, Claro Brasil realized that the creation of more accurate credit scores with the information available from prepaid customers has enormous value for its strategy and for this reason it has invested heavily to use more analytical intelligence, through more advanced statistical and computational mathematical techniques, with more data and taking full advantage of its analytical tools.

THE INTERNAL CONTEXT

CLARO BRASIL: GIANT AND INNOVATIVE

Claro is one of the largest telecommunications operators in Brazil, leader in the Pay TV market, with 49.2% of market share. On the VOD platform it reached 60 thousand titles and more than 1 billion transmissions in 2019 and remains the leader in the Brazilian market. Also leader in Brazil in broadband, with 9.4 million customers and leader in growth of postpaid mobile telephony. There are a total of 54.5 million mobile customers and total revenue of US \$ 10Bi per year.

Even though it is a giant operator and market leader, the company's positioning is one of innovation. With the slogan "You deserve the new", Claro has in its strategy innovation with priority and the use of data intelligence is one of the ways for this innovation.

This ambition of a giant to be innovative brings many internal challenges, because changing the traditional ways of doing business, when the results are positive and when it involves hundreds of processes and thousands of people, is very complex and even risky, but Claro assumes this challenge and always seeks to reinvent itself.

THE OPORTUNITY

The actions to upgrade customers from prepaid to postpaid have existed for some years and had several adjustments in the design of the public, however credit approval was limited to scores from external bureaus, which did not guarantee the customer's permanence with payment over time. The more aggressive sales targets forced a loosening of credit approval, an option that is not necessarily advantageous because it affects negatively the payment performance indicators in the future. Over time, sales volumes have been seen to increase, but defaults have also increased dramatically and customer retention has decreased, decreasing the profitability of upgrade actions.

Another important point in this process is that the selection of the public was based on premises of potential sales, while the approval of the customer's credit was carried out *a posteriori*, that is, only after the customer's acceptance the credit was verified. The prequalification of this public had prohibitive costs, since it would imply a very large volume of inquiries in credit bureaus, before attempting any sales action. In this way, the efficiency of the sales channel is also strongly impacted, as in the *a posteriori* verification process there is always a significant loss between the customer's acceptance and the actual sale.

Thus, the conclusion was that if it were possible to generate a credit score based on mobile phone usage data with high enough accuracy, there would be gains in: reducing the cost of

credit inquiries in bureaus, increasing sales volumes, reduction in default rates and increase in channel efficiency.

THE INTERNAL CHALLENGE

The development of such a solution in a traditional method of work in a large company like Claro faces many difficulties, such as:

A. Development time of the project is quite long: preparation of the databases is quite long and complex, development of the scores is also long until satisfactory results are obtained and implementation in production of development is somewhat complex, this makes the entire development and implementation cycle take a long time and therefore has a high cost for the company

B. Insecurity in relation to changing consolidated strategies: The team responsible for credit tends to rely heavily on credit bureaus models, as they are experienced institutions with long expertise on the subject. Therefore bringing all the development of a credit model into Claro brought insecurities regarding the possible quality of delivery, in relation to the maintenance of the model and mainly in relation to the need to use advanced machine learning techniques. In Brazil, at the time of the development of this project, the machine learning were still much discussed in the credit sector, because they are black box type, that is, difficult to interpret and because they have a higher risk of instability over time.

C. Insecurity in relation to selected audience: the sales teams have been working for a long time with audiences selected by market credit scores and as cut criterion with these models was reduced, sales conversions increased, because in general, audiences with higher credit risk have more appetite to buy, since they have fewer options in the market. For this reason, there was a fear that a new model of credit selection would bring customers that are more difficult to convert. Therefore, even if there was a result of longer permanence of customers and, therefore, a greater volume of customers in the long run, sales teams would see significant sales losses in the initial moment.

To overcome these challenges, we opted to use concepts of agile project developments. These methodologies emerged for systems development and in recent years have gained relevance on all the organization's work fronts, from adaptations and evolutions in each application.

DEVELOPMENT OF THE LIGHT CREDIT SCORE

FIRST STAGE OF THE PROJECT

The project was developed in different stages, always following the learning of agile work methodologies. The first stage was built on the concept of minimum viable product (MVP), that is, a simplified and aligned first internal credit score was created and implemented between all areas involved to test the real result of the approach.

In this MVP stage of the project, we followed the following phases:

1. Definition of priority variables for mathematical modeling: starting from the empirical knowledge of the representatives of each team, a prioritization of the data to be structured was created

2. Data preparation: starting from existing tables that had priority variables, without new data, just creating features derived from existing variables
3. Mathematical-computational modeling: to simplify the development and maintain the model's explainability, a simple decision tree was chosen to be used, so that everyone involved could easily understand what was being applied
4. Implementation in production: as the MVP credit score per decision tree considered only 4 variables, the processing was very simple and for the first tests, the model update was monthly and manual, performed by the Analytics area directly

All phases were followed up in recurring meetings with people from the sales, marketing, analytics and credit areas, being fully developed by the analytics area, which had already had expertise in the development of advanced prediction models, but which until then had not acted in credit models. This first delivery took 45 days to complete the score.

The objective of the first delivery would be a simple minimum viable product (MVP), but with sufficient results so that the areas involved could assess the potential of the project, therefore, for this phase we started with a few variables, which were already organized in datasets, all referring to registration, usage and top-up data.

The target of the model (output variable) was the first payment default, so that the evaluation of results after implementation was simple and quick.

Of the variables tested initially, only 11 showed some statistical relevance and after modeling by decision tree, only 4 variables were sufficient for the result of the internal credit score to be better than the bureau score. These variables proved to be strongly correlated to default, in an independently valuation.

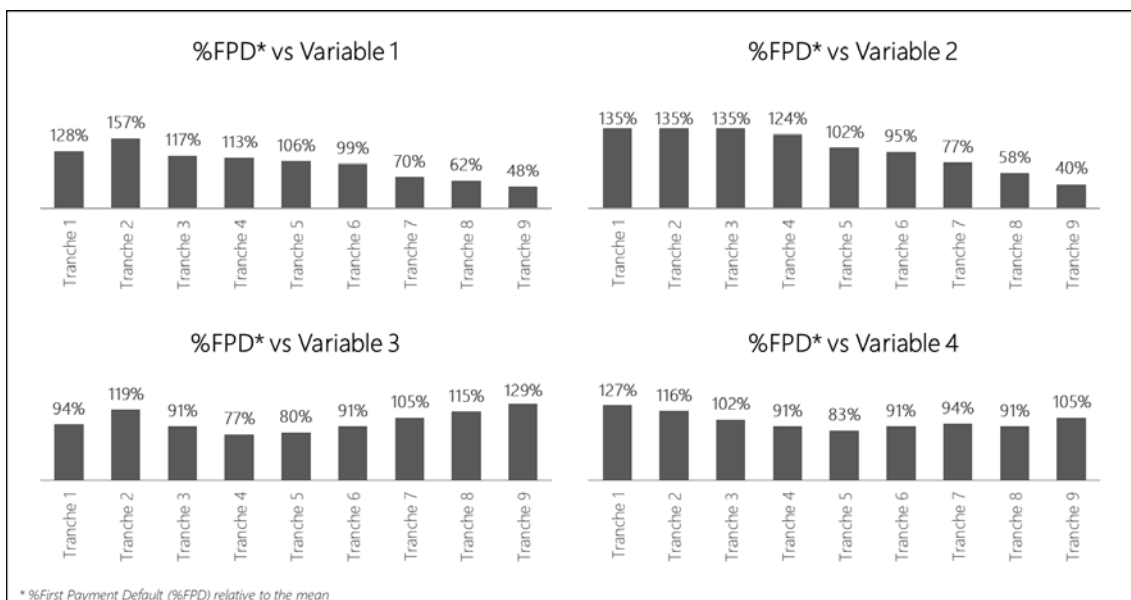


Figure 3. % First payment default relative FPD to the mean versus the four variables used in the decision tree.

The internal credit score (MVP1), based on decision trees, had an accuracy 8% higher than the market model and a KS 88% higher (The Kolmogoro-Smirnov). This effect happened

because there was a zone of instability in the external model, in which the probability of default increased, while the real default rate decreased. This zone coincided with the scores in which the bureau classified customers with little information in the market. In the internal model, the probabilities and results of bad rates always followed the same growth trend, with no inversion regions, which guaranteed a higher KS and ROC.

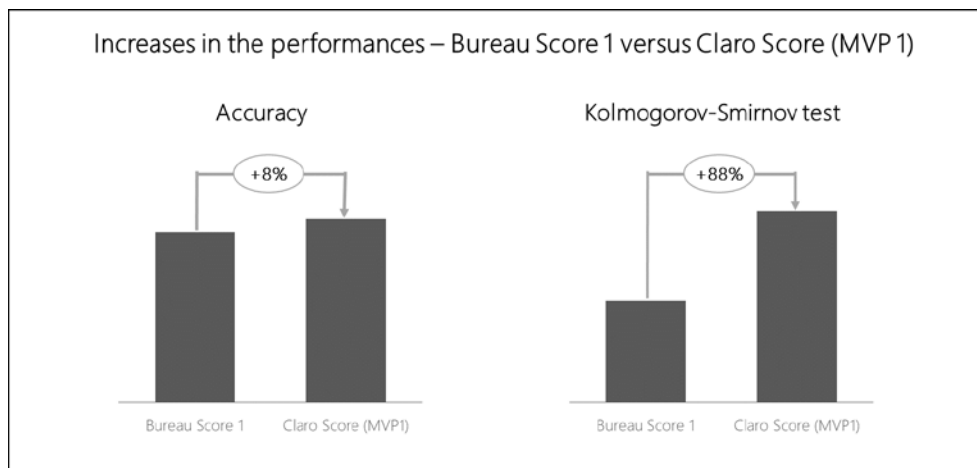


Figure 4. Increases in the performances (accuracy and KS) comparing the Bureau Score 1 versus the Claro Score (MVP 1).

From that moment on, KS was listed as a priority indicator of comparison between models. The Kolmogorov – Smirnov (KS) is one of the most used performance evaluation measures in the credit market in Brazil. This indicator measures the ability to distinguish the “good” from the “bad” payers and it is calculated as the maximum difference between the accumulated distributions of “good” and “bad”. The indicator ranges from 0 to 100% and the higher it is, the greater the capacity for separation between “good” and “bad” customers through the score.

SECOND STAGE OF THE PROJECT

The result of the first MVP stage was quite satisfactory and because it was developed in a partnership with all areas, the teams' insecurities were overcome and the development cost was very low. This first result made it possible to structure a multifunctional squad with full time dedication by representatives from the credit, sales, marketing and analytics teams so that new models could be developed with greater accuracy. The task was always conducted following agile methodology with the guidance of an agile master during all sprints.

This new stage had a higher cost and was longer, altogether it was another 120 days of work until reaching the optimal results of the score, using all the variables that the group had prioritized, through the creation of new specific tables for the project and testing various machine learning techniques in different sets of validation and out of time. In this second stage, more credit score performance was sought using more data and advanced techniques, with more robust model assessments.

In order to assess the ideal prediction target, several non-payment time scenarios were designed, varying between days of delay and the reading time space in order to optimize the quantity of options for study without losing the quality of prediction. The usual thing is to work with a performance of ever90M12 (some delay over 90 days in the next 12

months), however the post mortem validation would be too long and we tried to evaluate the behavior of more anticipated results. The evaluation of ever90M6, that is, in the next 6 months, was already enough to detect what would happen during the 12 months.

For the history of information to be tested, several data marts were built by subject, which also included derived variables (examples: participation of a certain type of connection in the total, influence of a certain operator in the customer's contact network, variations in use over time, others). The variables considered the prepaid life history, for example: top ups, usage, services purchases, demographics, social network links, etc.

To maximize the results of the models, the stage of preparation and selection of variables was quite extensive, always using the statistical techniques of analysis, to reduce risks of results with bias or unstable, mainly in logistic regression.

1. Variability Analysis: Some numerical variables were highly concentrated in a single value, for example, the history of complaints was null for almost all observations. Variables with 95% or more of the observations in a single value were discarded. Analogous criterion was used for the binary variables.

2. Correlation with the response variable: The variables selected in the variability analysis step are subjected to the correlation test with the response variable through the Information Value. In this step we select only the variables with a minimum correlation value with the response (IV) greater than 0.015, in this way we are guaranteeing that the final variables are those that will have the greatest contribution to the prediction of the response.

3. Multicollinearity (Correlation between covariates): Multicollinearity analysis was performed using the VIF indicator (Variance of Inflation). Variables with VIF greater than 10 were discarded.

4. Linearity and categorization: In the categorization stage, we used the WOE indicator (Weight of Evidence). When we choose to use a variable in its linear form, we analyze the WOE in bands to guarantee the monotonous trend, in case of a non-linear relationship we use transformations in the explanatory variable seeking to adjust to a linear and monotonous trend.

5. Transformation of variables: To avoid problems of non-linearity and outliers, the numerical variables were categorized by quartiles. Then, adjacent categories that did not differ in relation to the response variable were grouped.

6. Selection of Variables: Finally, for the logistic regression models, the "stepwise" procedure was used to define the variables of the predictive model. For the decision tree and "random forest", no additional procedure for selecting variables was performed.

With the evaluation of information value, there were two variables found with a very high relevance and that managed to have high power of discrimination. From the business point of view, these variables explained the customer's behavior and that they should be understood as customer segments. A segmentation was then created, with the objective of defining subsets of the population based on information blocks with behavioral characteristics, following the business perspective. In this way, four segments were created, which are detailed below, using the two variables:

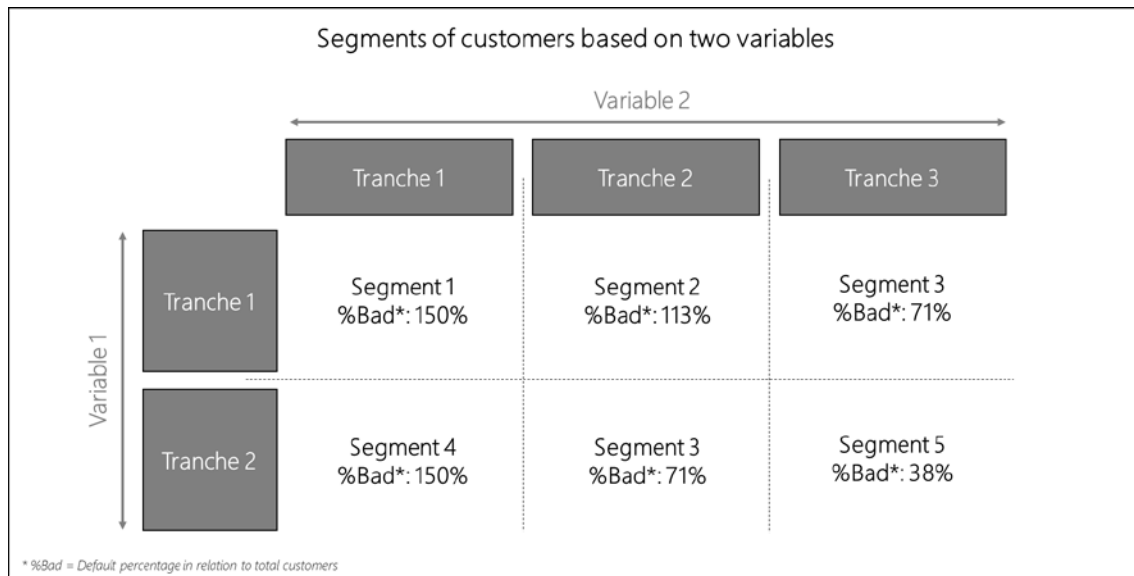


Figure 5. Segments of customers based on two variables and their % default percentage in relation to total customers.

To improve the lift, construction of the logistic regression models was segmented, so that five different equations were built at each stage of development. In addition to logistic regression, Decision Tree models were also built, where the result is a set of rules created automatically with breaks that maximize the discrimination of the target variable. The "Random forest" technique was also used, which consists of the creation of several classification trees. Each of them is constructed with a random sample of the observations and the variables considered in each partition are a random sample of all the variables considered.

Both the decision tree and the random forest are little affected by non-linearity, so the stage of preparing variables for these techniques could have been simplified, however the logistic regression is more sensitive to the presence of "outliers" and collinearities and because it is one of the techniques used, the well-developed variable preparation stage was very important.

The modeling was based on 3 million observations, partitioned into two subsets: the development with 70% of the observations, and the validation, with the remaining 30%.

The development of the models were on the SAS miner software. From the variables selected and available for modeling, the model estimation process begins. In this step, the analysis cover the combination of all simultaneous variables.

Following are the results obtained for the developed model. In order to assess the discrimination capacity of the models, the non-parametric statistical test, the Kolmogorov-Smirnov test and the Gini and ROC coefficients were used, in addition to the PSI to assess stability.

In parallel to this internal development, the credit bureau developed a new customized score with market data for the upgrade from prepaid to postpaid. The result of this new external model became the objective for the performance of the new internal models that would be developed next. In addition, negotiation with the bureau allowed all potential

customers to be prequalified, within acceptable costs, breaking the paradigm of *a posteriori* evaluation.

After the development of the new internal credit score, the gain in the prediction performance was evaluated by adding the new market score, reaching a blended credit score.

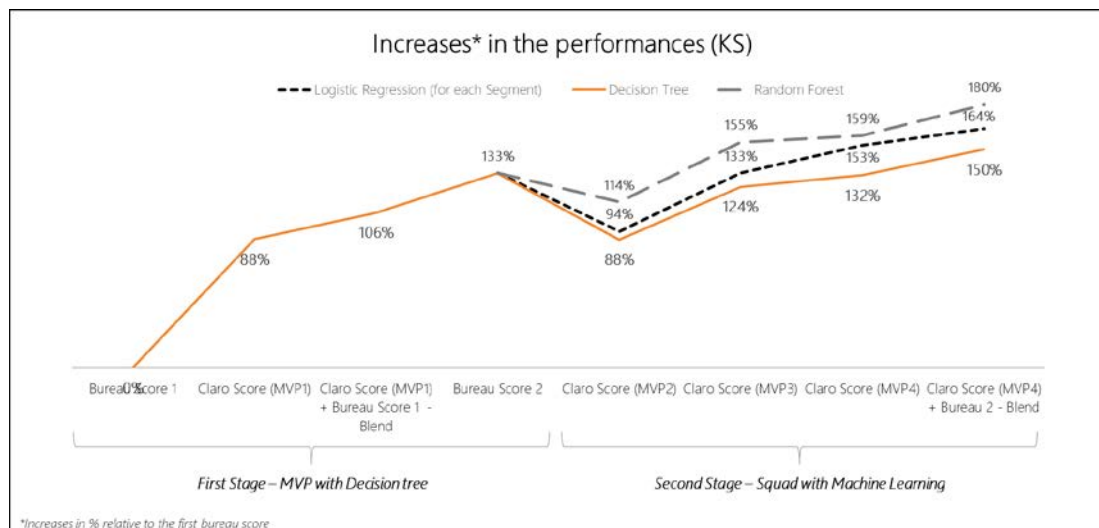


Figure 6. Increases in performances (KS) along the project, in% relative to the first bureau score.

Based on the performances obtained (180% greater than the initial bureau model), the model using the random forest technique, was decided to be used combined with the bureau's customized credit score. This blended model was very successful in selecting customers in the upgrade from prepaid to postpaid and from this model, people who previously had no access to postpaid plans now have this possibility, increasing customer satisfaction, increasing sales and reducing bad debt.

With such a positive scenario, the possibility of taking this solution to other companies was realized, as it became a very powerful solution to break the paradigms of the traditional credit score market, as it brought high discrimination power even for informal economy audiences, lower income and with no bank account, since all have data in telecommunications.

In order to take this predictive model to the market as a product, it was necessary to increase the number of people with available scores. For this, along with the credit score of the upgrade developed with the random forest technique, 3 other predictive models of behavior type that were already in production were added. These models had been created to direct the actions of relationship with the postpaid customer base of fixed services (cable and DTH) and mobile postpaid services.

With these four models and without the bureau's model, the Claro Score was created, a credit score based entirely on telecommunications data, with the capacity to discriminate in all types of audiences in Brazil. This new product led Claro to be a highly competitive player in a completely different market, opening up new possibilities for generating revenue, with very low direct costs and high quality products.

PROJECT GAINS

The implementation of the first version of the internal credit score, combined with the new model of the external bureau, led to a 1% higher sales approval and a 14% reduction in defaults. The final version of the Claro Score combined with the bureau's credit score had an additional 10% increase in sales and an additional 21% reduction in defaults, generating an impact of hundreds of millions of reais per year.

Variation (%)	Claro Score 1+Bureau 1	Claro Score2+Bureau 2
ΔApproved	+1%	+11%
ΔFirst payment Default	-14%	-31%

Table 1. Internal gains of the project in % of credit approval and % of FPD

This impact led to a drastic change in the company's default results, which previously had one of the highest delinquency results and today is one of the lowest with a consistent drop every quarter, even in a scenario of increased net adds well above the market, making Claro a benchmark on the subject.

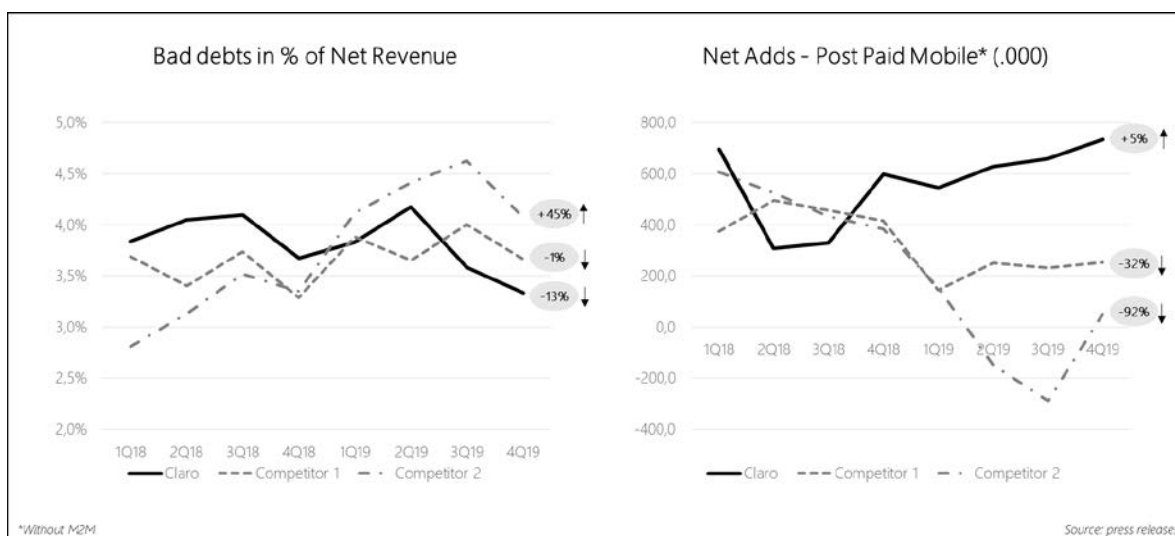


Figure 7. Results of Bad Debt and Net Adds - Carriers with the biggest postpaid mobile bases.

After launching the Claro Score to the market, relevant customers were gained in the retail and banking sector, in a new segment of activity for a traditional telecommunications company. As an example, in a client from another industry segment, there was a 7pp increase in the model's KS performance result, comparing the use of Claro Score with the traditional bureau model. This impact with no need for customization, which would probably increase this gain.

In addition to the possibilities of new business for Claro, this product will have important impacts on the Brazilian market, as it allows:

- Approve credit for part of the 48M of people in Brazil, who do not have information available in traditional bureaus, improving the lives of millions of people and helping the growth of the country's economy

- Improve performance of traditional credit models, either by approving more customers or by reducing bad debt, increasing the financial results of the companies that applied it

CONCLUSION

The potential for results applying telecommunications data in credit score is very high, but to capture this opportunity there were technical challenges of data science and organizational challenges, since Claro is a giant and winning company in the market.

In order to be able to carry out the project, the techniques of agile methodologies were used, so that the first partial deliveries provided security to the organization so that more resources were mobilized in the evolution of the project.

In order to prove the value of advanced techniques, it was necessary to compare the results of traditional techniques with the results of machine learning and thus it was seen that the gain of these advanced techniques was indeed satisfactory.

The financial results of the project were enormous, both increasing sales and reducing defaults, but in addition the possibility of bringing the Claro Score to the market as a product arose, bringing great gains to other companies.

After launching the Claro Score to the market, relevant customers were gained in the retail and banking sector, in a new segment of activity for a traditional telecommunications company. In addition to the possibilities for new business for Claro, this product will have important impacts on the Brazilian market, helping companies to improve results and enabling people to improve their lives.

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We especially thank everyone who participated in the development of the project. It was a few months of dedication, always with a high level of delivery.

We believe that there are countless possibilities to use telco data through data science to transform business, society and people's lives.

Our effort is to go beyond the connection.

To put all the best we have in one place.

To accompany new technologies, new economy, new ways of thinking, of relating.

And we continue to make our customers' lives more fun and productive.

After all, our business is to deliver the new.

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