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Creating a Product to Segment Donors and Predict Donor Churn for the Non-Profit Sector

The Impact of Paid Social Media Advertising on Financial Revenue for Non-Profits

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Abstract

The non-profit sector is dependent of spontaneous donations made by individual and companies. Non-Governmental Organizations (NGOs) do not know how to leverage on data about their donors, which can have a direct effect on an organization's success. In the present work, the team uses Machine Learning to segment donors and predict their churn probability using data from a NGO, to highlight the importance of targeted marketing strategies. Accordingly, the present study reflects on the advantages of paid advertising on social media in marketing campaigns, and their potential to positively affect the revenue of a non-governmental organization.

Keywords: Machine Learning, Business Analytics, Business and Data Analytics, Segmentation, Non-Profit Organization, Social Media Advertising

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I. Chapter I: Project Aim

1. Introduction

The following project is the result of collaboration between students of the master's in business analytics and the non-profit organization Assistência Médica Internacional (AMI), with the advisory of faculty members and external consultants from Accenture.

In the first part of this thesis, the team described, analysed, and curated AMI's dataset to develop a segmentation and prediction model, that aimed to improve the organization ability to retain donors and consequently increment monetary donations. In the second and final part, we study AMI's data, to understand if the use of paid advertising in social media has a direct effect on the revenue of an NGO. Starting by analysing the evaluation of their revenue over time and try to see if it is associated with the use of paid advertising in social media, according to the information given by the NGO itself.

2. Motivation and Literature Review

Although there have been many advances in technological tools that allow targeted actions, they are not often used for the social sector, with most campaigns running *ad hoc*. We can see that in other sectors, such as the private one, accuracy in campaigns is prioritized (Bodenberg & Roberts, 1990; Gönül & Shi, 1998). This is often due to the discrepancy of data in both sectors, but as data collection increases in NGO's it becomes possible to process that data and extract conclusions. Data can be used to increase their performance by being the basis for efficient marketing strategies.

The focus of marketing consists in "the exchange of values including time, money, knowledge, energy, goods and services between two parties" (Kotler, 1972 – pag.20). The correct application of marketing strategies can be determining for the success of an organization. In the non-profit sector the goal is not to maximize profitability by satisfying customer needs (Brennan and Brady, 1999). Instead, NGOs must focus on resource attraction (donors) and allocation (beneficiaries) (Sargeant, 2009). Their goal is to fulfil the community needs of the last-mentioned, by resorting to the first. In this sense, NGOs must rely on marketing strategies to maximize the monetary value raised from the donors, in order to achieve their ultimate goal of helping the beneficiaries.

More specifically, the non-profit sector relies on marketing to keep donors and encourage them to engage and maintain the relationship with the NGO. Additionally, communication actions can help to attract new donors - who can become potential valuable assets-, increase the organization's visibility, spread their mission, and promote their actions. The NGO will reach not only a national but also an international audience, thus strengthening its credibility, which is essential to increase the number of donations and volunteers. This expansion is crucial to guarantee the sustainability of the non-profit.

Though marketing actions present a lot of benefits, as previously mentioned, it can be challenging for non-profits to use them correctly and efficiently. According to a 2014 study by Content Marketing Institute, 61% of NGOs use content marketing [1]. However, only 35% claim these produce efficient results (Source: 2014 Nonprofit Content Marketers: New Research Trends, Content Marketing Institute), which can be justified by a multitude of reasons - discussed below.

[1] Content marketing is a form of marketing focused on creating, publishing, and distributing content for a targeted audience online.

The lack of funds can be identified as NGOs' the main challenge. Most non-profit organizations face the difficulty of having to constantly acquire funds. To develop an efficient marketing strategy, it is necessary to understand its requirements and costs. Most organizations develop strategic plans, but do not have the necessary funds to implement them. Hiring qualified people that have the knowledge to build a successful campaign is essential to understand how limited resources should be allocated, while guaranteeing the best results. Nevertheless, many NGOs do not consider the advantages of a more educated staff and, as they represent higher costs, and end up not prioritizing them in their decisions.

Secondly, **mass marketing**[2] fundraising is a method used by many organizations. However, it is also widely considered as outdated (Sargeant, 2009). Every day people are subjected to numerous marketing messages, which becomes saturating for the consumers. The overwhelming aspect of it will make the consumer lose interest and the company or organization will not be able to achieve the results desired.

Target marketing can help overcome the limitations above-mentioned. The use of direct strategies will help to not waist resources and allow the organizations to allocate them to the segments[3] that will effectively contribute to the achievement of their goals. "Direct marketing is about focused, targeted communication with strategic customers to promote the purchase of a good or service" (Thomas, 2007). This theory applies to the non-profit sector as well. Using targeted communication actions to strategic donors can increase NGOs' revenue and guarantee their sustainability. However, specifying the different needs and wants can be difficult without the proper information regarding each donor's historical behaviour and characteristics. That is

[2] "Marketing strategy in which a firm decides to ignore market segment differences and appeal the whole market with one offer or one strategy."
[3] Group of customers who share a similar set of needs and wants.

where data becomes one of the most important assets and one of the main challenges for a NGO. A strong, organized, and dependable donor data base can guarantee reliable results for any type of campaigns, including in social media.

More than two billion people use social media every day (Dean, 2021). These networks give the NGO the opportunity to be more informed about their target audience, build a stronger dataset and create a better. People are more aware of their social responsibility to help, and, in these technological times, the tendency is to do it through the easiest, less time consuming, and more effective way. From 2013 to 2017, the total fundraising from online giving increased significantly (Source: 2017 Charitable Giving Report, Blackbaud Institute). In a study conducted by Campaign Monitor, 39,5% of people said that they discovered the organizations they usually donate to on Facebook. The benefits of using these platforms can help not only to increase the visibility of the organization, by facilitating the deepening of the relationship with the donors through recurring stakeholder engagement (l Shin, 2018), but also promote charitable giving - thus increasing the NGO's profit.

During the past decades, social media platforms evolved, giving organizations the option to pay for advertising, which represented an opportunity. The use of paid advertising on social media is a means of targeting a predefined sub-audience by presenting advertising or sponsored marketing messages on different platforms such as Facebook, Google, and Instagram. Non-profits can resort to these sources to leverage on the benefits of the proposed marketing strategies.

As seen before, social-media presence can increase the organization's visibility, enhancing its recognition and creditability (Curtis et al. , 2010). Consequently, the engagement between the donor and NGO is positively affected, which ends up influencing the donor's behavior and the number of donations. Also, it gives organizations privilege perceptions about their audience and advertising campaigns. Facebook Insights[4] is a great example of a marketing insights platform. The paid version is considered an essential tool that will help the organization to achieve the maximum engagement and impressions, improve their top targets and narrow targeting settings.

The main difference between using paid and free advertising is that the latter allows the organization to decide specifically what groups to target directly with differentiated actions.

3. Problem Introduction and Research Question

The following work will prove that machine learning can be applied to automate donor segmentation in the social sector and predict a donor's willingness to donate again. Additionally, as targeted actions through different channels are suggested to lead to more prosperous outcomes, we will study the impact of paid advertising on social media in the non- profit sector. The proposed analysis will try to answer the following research question: “How does the use of paid Social Media advertising affect the revenue of an NGO?.”

[4] An analytics dashboard where you can track user behavior and post-performance on your Facebook businesspage

II. Chapter II: Creating a Product to Segment Donors and Predict Donor Churn

1. NGO Presentation

This project uses AMI's data to create models capable of being generalized to other NGOs. AMI is a private Portuguese organization whose mission is to “provide humanitarian aid and to promote human development” (AMI: Vision, Mission and Values 2021). Although AMI has supported over 10 000 people in Portugal through 15 social facilities, the organization is globally oriented, having carried intervention activities in 82 countries. As per mentioned by the NGO's representatives, it is composed of a small technical team, most collaborators work full-time and have non-technical background and little experience in computer science.

2. Context and Problem Definition

AMI has around 70 000 donors - 93% and 7% companies - and a vast majority of Portuguese contributors (99%). Although the foundation relies on monetary donations to maintain its activity, there is a notorious absence of recurrence: donors are unlikely to donate more than once. The lack of regular donations, and consequential financial instability, challenges AMI's viability. To increase monetary contributions, the NGO should grow the number of active donors - those who not only registered, but also contributed monetarily -, the number of donations and the amount donated per individual. As a result, the following project scope wasdefined:

- **Create a product to segment donors:** group donors based on similarities. Consequently, the possibility of predicting fall-backs will be improved by virtue of a better understanding of each donor's willingness to donate and his/her characteristics. Furthermore, it will allow to identify the donors who are more likely to make regular donations and target them. Ultimately, this will improve the ability to retain donors and increment donations.
- **Develop a model to predict donor churn:** The model will render, for each donor,

their probability of churn (the risk of not contributing to AMI again). This metric will be important to understand the willingness to donate, prevent churn, and allow more stabilityin the management of ongoing activities.

- **Create an interactive dashboard for data visualization:** This tool will help visualize data intuitively, providing easiness of interpretation. So, AMI's managers will be able to extractlessons and make data-driven decisions.

3. Data and Methodology

3.1 Data Description

The information was extracted in September 2020 from the NGO's own Customer Relationship Manager (CRM), where inputs are made by all business areas and the outputs are used by the departments of Communication, Image and Sensibilization, and Marketing. It contains details on the individuals and companies registered to AMI since 1990, as well as information about the donations, including their value and type (monetary, volunteering, goods, or services). Following General Data Protection Regulation (GDPR) rules, all the data delivered was anonymized and, therefore, could be used with no restrictions. It is recorded in six excel files containing only active donors.

Before an in-depth review of these records, it is relevant to establish two important distinctions. First, AMI can receive both monetary and non-monetary contributions. The first will generate a monetary flow, therefore including sales, donations, and funding. For the latter, the value of the offer is evaluated by AMI considering the time granted by the donor, in case of volunteer work, or the value of the good or service provided. Additionally, we should distinguish potential contributions from the ones that are finalized. AMI may contact previous donors to assess their interest in participating in new initiatives. If the donor does not respond, it will be classified as "potential".

3.2 Exploratory Data Analysis

With the intent of gaining a better understanding of the data provided, an Exploratory Data Analysis (EDA) was performed. The main purpose is to understand the data prior to making any assumptions that might affect future decision making. It focuses on finding relevant patterns, correlations, outliers, and mistakes. To simplify interpretation, visualizations were created using the “matplotlib” and “seaborn” libraries in Python. The inferred conclusions

from the current analysis are useful to support the decisions on the procedures to fill missing data. The general approach to dealing with missing values started by defining a threshold of 70%. Following GDPR rules, AMI can only contact individuals who gave their consent - hence, records whose consent date is not Null. Consequently, AMI only has permission to approach 0.17% of their single donors, blocking the implementation of targeted communication. Since this is a legal requirement, it cannot be deleted.

(i) Analysis at Donor Level

AMI provided data on 62 032 single donors and 3 164 companies, made up of their characteristics and demographics. However, from a total of 31 variables regarding information on individuals, as per the established threshold, only 14 variables were considered usable. In reference to the companies, we preserved 10 out of the original 14 features. Thus, decisive characteristics that could help improve segmentation (individual's age or company's sector) were disregarded. The amount of missing data is one of the biggest obstacles to the project - addressed again in section IV - and must be considered throughout all decisions.

There is a balanced distribution of donors by gender (51.8% men, against 48.1% women). We can also assume that AMI's appeal is mainly national: 99.75% of single contributors are Portuguese and only one company is foreign (Spanish). On average, an individual will donate 130€ to AMI in their donor journey, and a company 3 652€ 1. The total value offered by a company varies significantly, ranging from 1€ to 4 103 803.93 €. Most single donors (91.8%) are not registered as "AMI Friends", a loyalty program that encourages frequent donations, and 3.5% of companies partake in this initiative. AMI allocated every individual that did not have a known registration date to 1990, ergo the peak in enrolments in that year. Registration sources were grouped into 13 categories for a simpler analysis of its impact.

(ii) Analysis at Donation Level

Potential Contributions

AMI initiated the recording of potential contributions once the NGO transitioned to CRM, in 2018. Since CRM implied a higher granularity and maintenance of information, data quality improved. However, pattern recognition is hampered by the low number of observations - there was only one full year of data (2019) at the time of the analysis. Most contributions are set as "Lost", most likely because AMI makes untargeted contacts, automatically creating leads that do not generate response. This enhances the value of the present project: targeted decisions on segments help trigger actions by the donors.

Finalized Contributions

These records were either imported from AMI's old database, or already had a receipt associated, indicating the transaction was completed. These contemplate 170 750 logs from individuals between January 2004 and September 2020. As for companies, the team had access to information updated in February 2021 to improve model performance. It portrayed a total of 16 979 company contributions starting in 2004. Less than 50% of the individuals in AMI's database contributed at least once during the time frame mentioned. The maximum number of contributions made by a donor was 399. On average, each person donated 6 times and each company 4 times. However, most are one-time donors (61% of single donors and 57% of companies). The number of contributions per year has been tendentiously decreasing since 2011. GDPR rules restricted proactive contacts to subscribers to raise awareness and propose contributions, aggravating this trend. On average, a person will assist AMI 125 days after the previous contribution. Over 90% of donors had not made any endowment in the past 1.5 years, at the time of the analysis, coherent with the fact that most of them are one-time donors. Over 99% of contributions from individuals (60% for companies) refer to donations -voluntary transfers of money. The average value of received from individuals is of 54€. If we consider only non-monetary contributions (goods and services, volunteer work, visibility, and recycling), this comes up to 718€. As for monetary, the average value collected is 50€. The average value of a giving made by a company is

1 137€ and has been increasing since 2018. Monetary ones are lower (932€) than non-monetary (1 489€). The number of contributions made by a donor and their value have a correlation of –0.04, indicating independence.

3.3 Methodology

To achieve the goals propositioned in subsection 4, we will resort to ML algorithms. Their application requires an understanding of the data used, as well as its cleaning. The decision on the best models requires the testing of multiple algorithms and the comparison of their outputs. The final verdict will be based on predefined measures - suitable to each algorithm - and important criteria, according to the project scope.

3.4 Pipeline and Data Preparation

(i) Data Cleaning

Once data ingestion was finalized and information from the different sources was joined, it was prepared for the model. Consolidation and cleaning of the data involved the deletion of outliers, including errors - for instance, donors registered in 1930 (prior to the NGO's foundation) - and numerical variables whose z-score 2was higher than five. Missing values were filled according to context inferred internally and, when necessary, an external data source, the Iberian Balance Sheet Analysis System (SABI)3 was used to get firmographics on the companies. We transformed the data types to meet the model's requirements and performed feature engineering, including upstream categorization (grouping values into wider categories) and the creation of additional variables (e.g., days since donors' last contribution). Finally, we resorted to the "scikit-learn" library to encode categorical variables (one-hot-encoding) and standardise numerical features (standard scaler).

(ii) Feature Selection

After feature engineering, 494 variables integrated the final table. Feature selection followed a multidimensional approach that combined analytical decisions - deleting attributes based on the lack of data quality or high levels of correlation - and functional evaluation, based on AMI's experience. It is proposed as functional because it considers a practical interpretation of the problem, centring on an intuitive view of what characteristics should be key in a segmentation. At last, we tested different combinations of variables and selected the one that provided the best result4.

4. Model Application and Evaluation

4.1 Segmentation Model

(i) Algorithms attempted

Since there were are no previously defined clusters, we can consider there is no target variable for the segmentation. As such, we tested several unsupervised learning models5.

The first attempt used DB-Scan [2], a density-based clustering algorithm (Scikit-learn 2021). For this algorithm, a minimum number of donors is defined for each cluster. Similar donors are grouped into the same cluster, and those that are in regions with a density below the minimum threshold are marked as outliers. However, even with a low number of necessary neighbours for each cluster, most donors were classified as outliers, which is hardly interpretable.

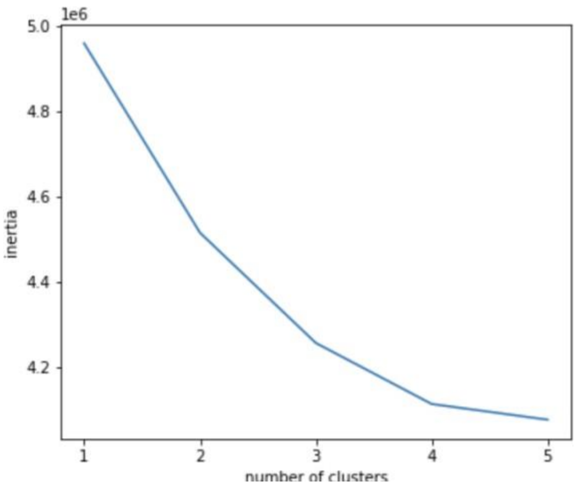
K-Means [3] is a fast, widely used method that minimises the inertia (maximizes the cohesion within the same group), by partitioning the observations to the clusters with the nearest mean (Scikit-learn 2021). The algorithm was experimented with multiple combinations of variables and the elbow method (Soppin, Ramachandra and Chandrashekar 2021) was applied to derive the optimal number of clusters for each trial. PCA [4] was applied before K-Means, for a two-dimensional representation of the model, facilitating the comparison of the performance of the different sets of attributes (Brownlee 2020).

(ii) Model Evaluation

The best option should be heterogeneous inter-cluster, whilst coherent intra-cluster, so that it is easy to characterize a donor based on the group he/she is inserted in. Separability and interpretability are key when evaluating the model. To ensure these, two-sample t-tests and one-way ANOVA were employed at each attempt. The former evaluates if feature values were different from one segment to another, by examining whether the differences are statistically significant (P-value< 0.05) (Webster 2013). The latter tests the null hypothesis that two or more groups have the same population mean. The silhouette-score - a similarity score where "the best value is 1 and the worst value is -1" (Scikit-learn 2021) - was also considered when comparing the distinguishability of the outcomes, i.e., whether the object resembles its own cluster and not the others. Finally, a homogenous size of the clusters was used as cohesion indicator.

(iii) Model Decision

The best model focuses mostly on interpretability, to be user-friendly for the client. It outperformed the others for all metrics [5], but the silhouette-score. Standardizing the data can make separability more difficult, which could explain this lower score. The final model used 4 different clusters and a set of features[6] and characteristics heterogeneous enough to embark efficient marketing actions. Cluster 0 ended up with approximately 7k donors, 1 with 5k, 2 with 24k and 4 with 31k. Cluster 0 was found the persona most important to retain, as they donate more than once and a relatively high value in their lifetime as donors.



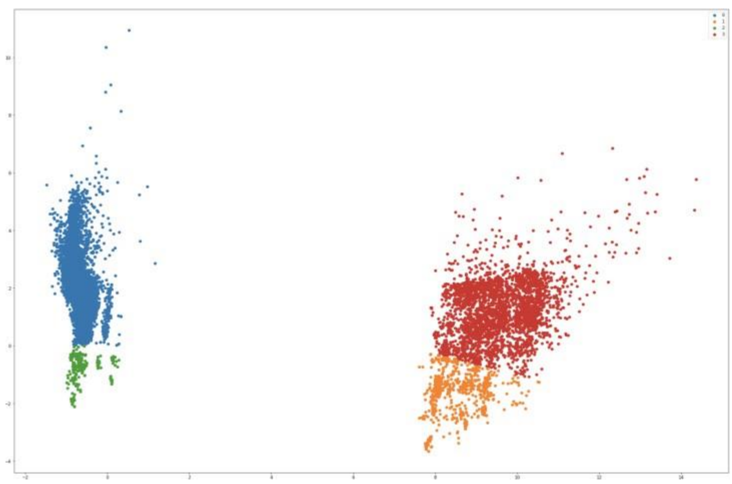


Figure 1 Elbow method with selected features. **Figure 2** Clusters from K-Means application (k=4) with selected features.

4.2.Churn Prediction Model

(i) Churn Definition

For exiting prediction, the team used a supervised model7 where the target variable should indicate whether the donor is churned. Since AMI did not have a definition of churn prior to the project, the team defined, together with the NGO, a list of rules for this classification. First, only people who contributed with a monetary donation at least once should be eligible for this evaluation. Then,

- If the donor only donated once, then the time since last contribution was taken into account. If the number of days since that donation was higher than the average number of days between contributions for all donors, the donor was classified as churned.
- If the donor contributed multiple times, the team compared the last contribution to the donor's usual frequency. If the number of days since the last time the donor contributed was higher than the average number of days between contributions for that donor, he/she was classified as churned.

(ii) Pipeline for Classification Model

Most of AMI's givers are one-time donors and, consequently, have churned. As such, our data is imbalanced. We employed synthetic minority over-sampling technique (SMOTE) (Imbalanced-Learning 2021) [8] to generate the same number of observations for the minority class (not churned) as for the majority class (churned), so the model can learn better. Synthetic points are generated from the potential points that underly the pairs of actual data, by assuming they would follow a similar distribution, i.e., anything between 2 points from the minority class is likely to be from that class too. The resulting samples were used to train multiple classification models. The team used grid search [9] to decide on the optimal values for a set of hyperparameters including the penalty to apply (L1 or L2), to avoid overtraining (Géron 2017) (Scikit-learn 2021).

(iii) Model Evaluation

The model is designed to identify new donors who are at risk of churn. The data was split into a training set and a test to evaluate the capability of generalizing the model to donors not used to train it.

Accuracy and precision were chosen as the most relevant metrics to indicate the quality of the predictions. The first returns the percentage of correctly predicted points out of the total points, the second the percentage of points predicted as positive (churned) that are correct (True Positives). If a person is at risk of churn but is not predicted, AMI will apply to them undifferentiated actions. If they are wrongly predicted as churned, AMI will use part of their resources for targeted actions and increase their costs, thus False Positive cost is higher.

(iv) Model Decision

Since the results for the baseline model (Logistic Regression [10]) and the more complex ones (XG-Boost [11]) were not significantly different, the team opted to use the Logistic Regression. This still allowed to get a precision of 99.9% and accuracy of 99.73% for the test set, while performing faster and implying lower costs than the other options. We should consider that the results of the model are highly influenced by the fact that the dataset usable for the churn prediction is very small. For the test set, a total of 5 285 donors were predicted as churned, versus 5 213 not churned (only monetary contributors considered). As AMI considered that the probability of churn would be more useful for their business decisions than a binary classification, the final output was changed to meet those needs.

4.3.Fairness and Bias

An important part of the evaluation of the model is understanding if our classification model is fair and unbiased. We used two variables that could create an unfair model: gender and region. We calculated the recall parity with “male” and “Lisbon” as reference values, using the “Aequitas Audit Toolkit”. Balanced outcomes between the different categories of the chosen variables lead us to believe the outputs of the model are fair. The segmentation was not accessed in this metric because it is, by definition, an agglomerate of similar individuals (intra- cluster) that should be addressed differently (inter-cluster).

III. Chapter II: The Impact of Paid Social Media Advertising on Financial Revenue for Non-Profits

1. Addressing the Research Question Problematic

Using the models developed, AMI can segment their donors and find the probability of them to churn. Like we stated, the capability of segmenting the donors will increase the effectiveness when developing marketing campaigns.

However, there are different channels that an organization can use to implement targeted communication actions. As we saw above, Social Media platforms are a promising approach when it comes to improving marketing strategies in the non-profit sector. More specifically, an organization can leverage on paid advertising to getter valuable insights about their donors, target specific groups of people and consequently increase the number of monetary donations.

In this chapter, we will evaluate the impact of the adoption of paid social media campaigns by AMI, as a representation of its potential to achieve the above-mentioned goals for the non-profit sector.

2. AMI Use Case

1.2 Contextual Background

It is essential for any organization to keep up with its consumers and evolve with the times, to guarantee its success. Given that AMI is considered one of the most influential Portuguese non-profits, they recognized this necessity and, accordingly, adopted social media as a part of their strategy as its tendency grew in our society. In 2009, the organization joined Facebook with the goal of gaining visibility, promoting their campaigns, and eventually have more knowledge about their donors.

However, due to lack of experience per part of AMI’s team, they did not take full advantage of their potential. To improve the results, in 2016 the NGO acquired a Social Media Manager to join AMI’s marketing department. The manager proposed marketing strategies and advised the organization to start using paid advertising on different platforms, such as Facebook, Instagram, and Google. According to AMI’s team today, this was the turning point for the marketing department.

1.3 Data Description

As such, to decide on the best strategy to answer the research question proposed, we should consider the conclusions and understanding of the data from the exploratory analysis previously made. Additionally, we should recall that AMI's dataset includes data from 2001 to 2021. However, some managerial issues led to problem during data migration that resulted in the loss of data for the year 2002.

As previously stated, AMI’s data can be separated into two levels: details regarding each donor, and information on each contribution. Since our goal is to are evaluate the impact on revenue, we will focus on the second part, to evaluate the evolution of the value of the giving’s to AMI.

3. Methodology and Results

3.1 Data Preparation

3.1.1 Total Revenue per year Calculation

To calculate the total revenue for each year, we considered the value donated by both individuals and collective donors. There was no distinction made between the two types since AMI does not differentiate them when developing their social media strategies.

$$total\ year\ revenue = \sum Value\ of\ contributions$$

For the current analysis, we analyse the solely the evolution of the value of donations because they are the basis for AMI's sustainability, therefore the ones that will have an impact in this analysis. We did not take in consideration any other source of revenue, such as Governmental subsidies.

3.1.2 Revenue Growth Calculation

After calculating each year total revenue, in order to draw conclusions, we compared the values for the different years, and calculated the percentage of annual revenue growth, using the following formula:

$$Revenue\ Growth\ (\%) = \frac{(Current\ year\ revenue - Previous\ year\ revenue)}{Previous\ year\ revenue} \times 100$$

The methodology accounts for both positive and negative revenue growth fluctuations. A negative percentage indicates a decrease in revenue compared to the previous year. On the other hand, if the value is a positive percentage, it shows an increase of revenue between that period.

3.2 Analysis of revenue over time

When looking at AMI's calculated revenue growth per year[5], we can see that the biggest increase was between 2003 and 2004, when the revenue grew around 741579.6%. As a result of an emergency campaign, AMI received a large amount of donations. This campaign aimed to help victims of the 2004 Tsunami in India, one of the largest tsunamis on record that made more than 230 000 victims. Comparing with the other years, this revenue growth is unusually high. To prevent difficulty in the interpretability of the visualization, the outlier is not represented in the following graphic.

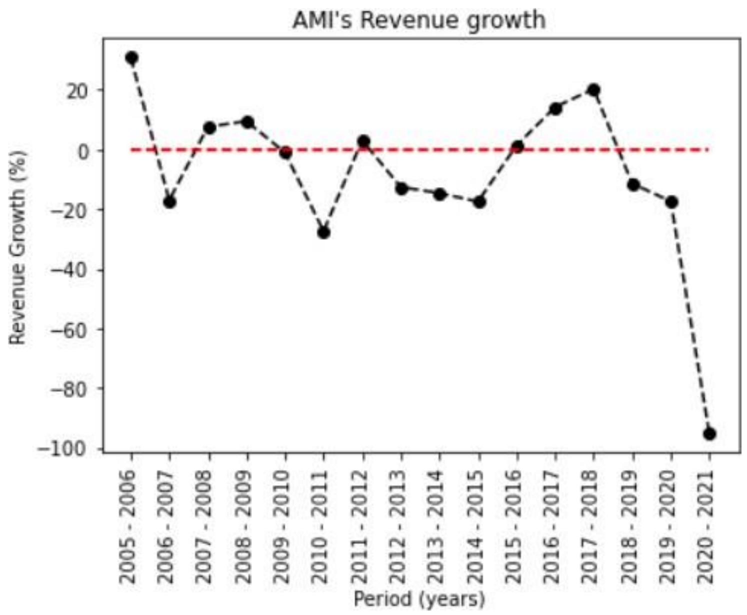


Figure 1- AMI's revenue growth between 2005 and 2021

Besides, from 2004 to 2015, AMI presented mostly negative values of revenue growth in most the years, with the exceptions of 2005, 2008 and 2009 that show a small positive revenue growth. During this period AMI did not possessed enough insights from their uses, therefore could not decide on more data-drive strategies, that would improve their results. Like it was previously explained is important for an NGO to develop a marketing strategy and allocate

[5] The specific values can be found in appendix.

resources in an effective and clever way. However, there are other factors that could have had a positive or negative impact on an NGO revenue. In the section *Implications and Future Work,* the stated some of those factors.

On the other hand, from 2015 to 2018, AMI had three years in a row with a positive revenue growth, relatively high. AMI changed two aspects that can justify this gradual increase of revenue. Firstly, like we saw in AMI's case, in 2016 the NGO started to use paid advertising in social media, as an advice of a recently employed Social Media Manger. The organization privileged the use of paid advertising, in different platforms, when developing marketing plans that led to successful campaigns. AMI noticed an increase of visibility and subsequently increase of donations. Secondly, AMI implemented a new Customer Relationship Management (CRM) system. This helped the NGO to start a donor-centric technique and allocate their resources effectively. Both initiatives contributed to better knowledge of donors and like it is possible to see a gradual increase of the revenue growth between those years.

However, from 2018 to 2020, this metric started to decrease again. During this period, AMI was affected by a lot of factors that had a direct effect on their revenue that could not be ignored. One of the most impactful changes was the implementation of GDPR in 2018, which made it illegal to contact donors that did not explicitly give their consent. For this reason, the organization stopped being able to reach out directly to a large amount of their donor base and had to replace old communication strategies, such as mailing campaigns, with untargeted actions.

Finally, the accentuated decrease between 2020 and 2021 can be explained by the fact that the data given by the organization to develop this work project only had information from the first months of 2021, which meant that most of donations made during the year were not taken into consideration.

3.3 Main Empirical Findings

As can be seen in the previous analysis, AMI presents different and accentuated fluctuations of revenue growth during the last decade. There are events that justify noticeable changes throughout the years. For substantial variations, it is easier to identify the main factors that motivated them - for instance, big natural catastrophes and the following emergency campaigns - yet, for smaller fluctuations the reason behind the increase or decrease of revenue is more difficult to recognise.

According to the analysis made, we can find an association between the moment AMI adopted social media and the positive tendency in revenue. For this reason, we can assume paid advertising on social media as one of the most relevant influences on AMI's financials. However, it is not possible to be affirm that it is the main reason for the variation since another factor could have had a major impact. From 2015 to 2018, AMI’s revenue growth is constantly increasing, but after 2018 the organization was faced with a significant revenue drop. While AMI kept using paid advertising and developing social media strategies, we can see that in certain situations it is not enough to overcome the negative consequences.

4. Implications and Future Work

The analysis performed is highly valuable for a non-profit organization since it underlines the importance of paid advertising strategies for building and achieving positive financial results. However, it also explains that it is not possible to do a causal analysis since that are numerous factors that are also relevant and had an impact on the variations of the financial revenue.

More than other industries, the non-profit sector must be aware of market or public mood changes. During the last decade, natural catastrophes, changes in the tax code, global economy, or a pandemic were all factors that had a direct impact on any NGO's revenue. In AMI's case, apart from those examples, they have two types of campaigns: emergency and programmed campaigns. Every year, there are peaks of revenue when a programmed campaign, for example during the Christmas season, occurs. These campaigns are essential for guarantying the financial sustainability of the organization since they can always rely on them. On the contrary, emergency campaigns can occur unexpectedly and completely change the revenue values of an organization.

For future work, organizations could also gain from evaluating the impact that social media has in different donors with particular demographic and behavioural characteristics, to pre-emptively understand the differences among donors, to perform directed actions.

Additionally, it would be important to apprehend if the non-profit sector can benefit more from lowering their costs or increasing their revenue, to find an efficient path to reach their goals.

III. Conclusion

This thesis explored the importance that applying an effective segmentation and marketing strategy can have in a non-profit organization.

We started by developing effectives model capable of segmenting AMI’s donors and predicting the probability of a donor to churn. These tools were delivered to AMI and will allow them to target specific donors and avoid losing them.

Using paid advertising will potentially be a factor that positively contributes to increasing NGOs' profit, as proven by the historical behaviour of AMI's revenues and the timing associated to their social-media presence. Combining this strategy with targeted communication actions, as the ones potentiated by the ML models proposed, can significantly change their results, and contribute to achieve the first and foremost intended goal: to increase their fundraisings.

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Appendix

1. Total value of contributions and Revenue growth of AMI from 2001 to 2021

Year	*Total Value of Contributions (€)*	*Revenue Growth between the current year and the next*
2001	49	0.0 %
2003	49	741579.6 %
2004	363423	2795.0 %
2005	10521084	30.9 %
2006	13775738	-17.0 %
2007	11433462	7.6 %
2008	12301176	9.5 %
2009	13474198	-1.0 %
2010	13337846	-27.4 %
2011	9682682	3.1 %
2012	9981411	-12.6 %
2013	8726081	14.6%
2014	7449823	-17.5 %
2015	6146507	1.3 %
2016	6227752	14.2 %
2017	7114703	20.3 %
2018	8561865	-11.4 %
2019	7588710	-17.4 %
2020	6269422	-95.1 %
2021	310290	NaN

1. REGISTRATION SOURCE GROUPS

Registration Source Group Name	*Original values included in the group*
OTHERS	'OUTROS'
CORPORATE PARTNERSHIPS	'Giro 2.1'
	'AMIARTE'
	'NBup'
	'AÇÃO FRESENIUS'
	'Pontos Meos Voluntariado'
	'PARCERIA'
	'BARCLAYS/CABAZ NATAL12'
ENVIRONMENT	'AMBIENTE'
	'No planet B'
TRAINING	'Formação aos voluntários'
	'FORMACAO'
	'REUNIÃO NÚCLEO'
	'SOCORRISMO'
SOCIAL CAMPAIGNS	'PRENDA SOLIDÁRIA/09'
	'AÇÃO SOCIAL'
	'Fundo Universitário'
	'Iniciativa ODS'
	'Taleigo Amigo'
	'Projeto'
	'Voluntariado Nacional'
	'PAPORTO'
	'PREMIO JORNALISMO'
	'AVENTURA SOLIDÁRIA'

	'Giving Tuesday'
	'MARVILARTE'
INTERNATIONAL CAMPAIGNS:	'Campanha FNAC Moçambique'
	'CAMPANHA ZIMBABUÉ'
	'CAMPANHA TERCEIROS'
	'MAILLING SRI LANKA'
	'Voluntariado Internacional'
EMERGENCY CAMPAIGNS	'CAMPANHA EMERGÊNCIA HAITI'
	'CAMPANHA EMERGÊNCIA MADEIRA'
	'Emergência Moçambique 2019'
	'Emergência Covid-19'
	'CAMPANHA SOS LÍBANO'
	'MAILING EMERGÊNCIA LÍBANO'
	'EMERGENCIA FILIPINAS'
	'MAILLING EMERGÊNCIA/09'
CHRISTMAS CAMPAIGNS	'MAILING NATAL 07'
	'MAILING NATAL 10'
	'MAILING NATAL 06'
	'MAILLING NATAL 05'
	'M. NATAL'
DONORS	'DOADORES 04'
	'DOADORES 09'
	'DOADORES 08'
	'DOADORES 02'
	'DOADORES 10'
	'DOADORES 97'
	'DOADORES 07'
	'DOADORES 03'
	'DOADORES 05'

	'DOADORES/NATAL/08'
	'M. DOADORES'
	'DOADORES 98'
AUCHAN CAMPAIGN	'CAMPANHA AUCHAN 06'
	'AUCHAN'
	'AUCHAN 10'
	'AUCHAN 09'
VOLUNTEER REGISTRATION	'ESPONTÂNEO'
AMI RESOURCES/DEPARTMENTS	'RECURSOS HUMANOS'
	'PUBLICIDADE'
	'REVISTA'
	'SITE AMI',
	'LOJA AMI'
	'FICHA AMIGO'
	'Noticias AMI'
	'Recrutamento'
	'Campanha face to face'
	'COLABORADORES'
	'ADMINISTRAÇÃO',
	'PLATAFORMA'
	'Órgão de Comunicação Social'
	'FICHA DE INSCRIÇÃO AA'
	'Departamento Internacional'
	'PRENDA AMIGA'
	'DEL NORTE'
	'DEL FUNCHAL'
	'DEL CENTRO'
	'Delegação da Terceira'
TMN Campaigns:	'PONTOS TMN'
	'PONTOS TMN MADEIRA'

'Pontos TMN MEO Pedrogão'
'PONTOS TMN MADEIRA'
'Pontos TMN Moçambique'

2. DBSCAN ALGORITHM

The Density-Based Spatial Clustering of Applications with Noise is an alternative algorithm to the K-means. It clusters data into high-density form free shapes surrounded by lower density areas. The procedure is usually based on Euclidean distance and a radius, ε. For an example x_i, surrounded by n_{min} points, it becomes a core point:

$$N(d(\bar{x}_i, \bar{x}_j) \leqslant \epsilon) \geqslant n_{min}$$

A certain point is said to be close to another if the Euclidean distance between the two points in minor than the radius, ε. All samples belong to a cluster. After accounting for all directly reachable points the remaining ones are considered *noise*. In the end we can visualize conglomerates of points surrounded by some noisy samples.

3. K-MEANS

K-Means is an unsupervised learning algorithm proposed by Thomas Cover and used for the first time by James MacQueen in 1967. James investigated a method for partitioning a basic sample into k sets in order to achieve an efficient within-class variance (MacQueen, 1967). Nowadays, the goal of this algorithm is to minimize the average squared Euclidean distance of objects to their cluster centers (Manning et al.), to acquire qualitative insights on data by dividing the information according to the similarities of each data point.

The less variation exists between clusters, the more similar data points are with the same cluster (Imad Dabbura, 2018).

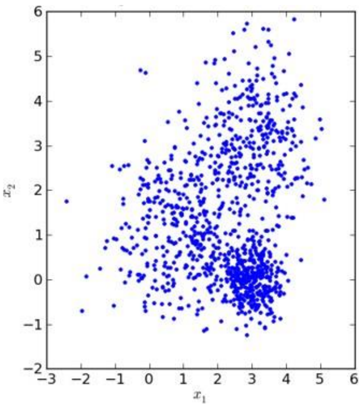

Figure 5 Example of unclustered data

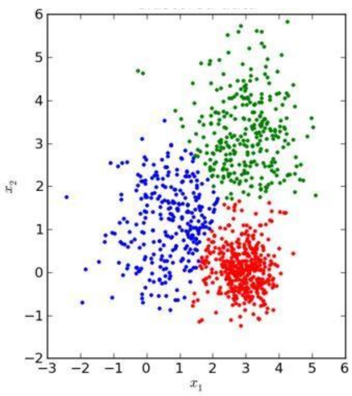

Figure 6 Clustered data after k-means algorithm

Above we can see a visual representation of the K-means algorithm and its purpose. The number of clusters is chosen prior to the implementation of the algorithm. It can be determined by different techniques such as the elbow method (Kodinariya & Makwana, 2013) and silhouette analysis. To conclude, K-means is one of the most used clustering algorithms due to how easily it can be implemented. It is a computationally faster method that produces tight clusters and find more sub-cluster if data larger cluster number is pre specified.

4. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal Component Analysis (PCA) can be considered as an unsupervised learning algorithm, commonly used for dimensionality reduction to help in important tasks, including, "visualization, compressing the data, and finding a representation that is more informative for further processing (Müller & Guido, 2016). PCA is an attribute aggregation technique, initially proposed in 1901 by Karl Pearson, that consists of projecting data to a new dataset with a smaller number of features and, although it is considered simple, it requires some strong mathematical assumptions (Mendes Moreira, C. P. L. F. de Carvalho, & Horváth, 2018).

A data projection consists of transforming attributes in one space (sources) to another (signals), while trying to keep as much as possible the information from the original set of attributes and eliminating its redundancy. PCA achieves this elimination of noise by combining the original features into new ones (the principal components) that allow for a reduction of the covariance, using matrix operations from linear algebra. High covariance of variables mean that they will influence the model in the same way, therefore should not be chosen together. In PCA, "each principal component is a linear combination of the original attributes" (Mendes Moreira, C. P. L. F. de Carvalho, & Horváth, 2018). The linear algebra used by PCA is provided by Singular Value Decomposition (SVD). Firstly, the mean of each dimension is calculated for the whole dataset (d dimensionns), used to compute the covariance matrix afterwards. Then, *eigenvectors* and corresponding *eigenvalues* are calculated and sorted, from highest to lowest. The predefined number (k) of largest eigenvalues are chosen to form new a dimensional matrix dimensional (d x k), used to transform the samples onto the new subspace (Dubey, 2018).

An Eigenvalue increases the Eigenvectors along their span by the value of the first, when transformed linearly (Adewumi, 2019). An eigenvalue (λ) of a square matrix (A) will do such that any transformation on it with an eigen vector 7 will equal the scalar multiplication of λ with A ($A7 = \lambda 7$ *where* 7 G 0) (Dadhich, 2018).

In sum, when using the PCA method, the components are ranked from the highest variance value to the lowest and selected by prioritizing the largest variances. The number of components chosen is based on a predefinition of that value, or when the increase in variance of the data when adding the component becomes irrelevant. By using this process, there is the guarantee that any feature that is not contributing significantly to the results is ignored and the model can benefit from the advantages of a smaller number of dimensions.

5. METRICS – T-TEST AND ANOVA RESULTS

ANOVA Results

	p-value
gender_Feminino	0
gender_Masculino	0
gender_company	0
gender_other	0,00011
AMI_friend	0
consent_boolean	0
total_value	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	0
registration_source_group_AUCHAN CAMPAIGN	0
registration_source_group_CHRISTMAS CAMPAIGNS	0
registration_source_group_CORPORATE PARTNERSHIPS	0
registration_source_group_DONORS	0
registration_source_group_EMERGENCY CAMPAIGNS	0
registration_source_group_ENVIRONMENT	0
registration_source_group_INTERNATIONAL CAMPAIGNS	0

registration_source_group_NATIONAL CAMPAIGNS	0
registration_source_group_OTHERS	0
registration_source_group_SPONTANEOUS REGISTRATION	0
registration_source_group_TMN CAMPAIGNS	0
registration_source_group_TRAINING	0
1st_value	0
avg_value_cont	0
avg_days_between_contrib	0
days_since_donor_last_contribution	0
everismonetary	0
total_contributions	0
region_Alentejo	0
region_Algarve	0,00577
region_Açores	0,00135
region_Beira Interior	0
region_Beira Litoral	0
region_Entre-Douro-e-Minho	0
region_Lisboa	0
region_Madeira	0
region_NOT FOUND	0
region_Trás-os-Montes e Alto Douro	0
region_Vale do Tejo	0
individual/collective	0
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	0
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	0
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	0
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	0

field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	0
field_description_ACTIVIDADES IMOBILIÁRIAS	0
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	0
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	0
field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES	0
field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	0
field_description_COMÉRCIO E VEÍCULOS	0
field_description_CONSTRUÇÃO	0
field_description_EDUCAÇÃO	0
field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	0
field_description_INDÚSTRIAS EXTRACTIVAS	0
field_description_INDÚSTRIAS TRANSFORMADORAS	0
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	0
field_description_TRANSPORTES E ARMAZENAGEM	0
field_description_individuals	0
field_description_not found	0
Legal Form_Agrupamento Complementar de Empresas	0,00683
Legal Form_Associação	0
Legal Form_Autarquia	0
Legal Form_Cooperativa	0
Legal Form_Empresário em Nome Individual	0,00683
Legal Form_Entidade Estrangeira	0
Legal Form_Fundação	0
Legal Form_Organismo de Administração Pública	0
Legal Form_Sociedade Anónima	0
Legal Form_Sociedade Unipessoal por Quotas	0
Legal Form_Sociedade por Quotas	0

Legal Form_individuals	0
Legal Form_unknown	0

T-TEST: Cluster 0 VS Cluster 1	*statistic*	*pvalue*
gender_Feminino	-53,1744	0
gender_Masculino	-95,6949	0
gender_company	1,43E+18	0
gender_other	-1,94184	0,05216
AMI_friend	28,35666	0
consent_boolean	-0,99153	0,32143
total_value	40,5415	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	39,29291	0
registration_source_group_AUCHAN CAMPAIGN	6,25992	0
registration_source_group_CHRISTMAS CAMPAIGNS	21,14016	0
registration_source_group_CORPORATE PARTNERSHIPS	33,78672	0
registration_source_group_DONORS	20,46315	0
registration_source_group_EMERGENCY CAMPAIGNS	24,8972	0
registration_source_group_ENVIRONMENT	31,77094	0
registration_source_group_INTERNATIONAL CAMPAIGNS	12,6955	0
registration_source_group_NATIONAL CAMPAIGNS	2,39966	0,01642
registration_source_group_OTHERS	-98,5558	0
registration_source_group_SPONTANEOUS REGISTRATION	46,18694	0
registration_source_group_TMN CAMPAIGNS	31,88278	0
registration_source_group_TRAINING	12,89019	0
1st_value	161,2823	0
avg_value_cont	-2,34313	0,01913
avg_days_between_contrib	-0,89154	0,37265
days_since_donor_last_contribution	159,5334	0
everismonetary	156,5473	0

total_contributions	52,39363	0
region_Alentejo	1,0014	0,31664
region_Algarve	0,51775	0,60464
region_Açores	3,80495	0,00014
region_Beira Interior	4,13714	0,00004
region_Beira Litoral	10,10547	0
region_Entre-Douro-e-Minho	-3,98539	0,00007
region_Lisboa	-5,77327	0
region_Madeira	7,37926	0
region_NOT FOUND	5,31359	0
region_Trás-os-Montes e Alto Douro	3,5627	0,00037
region_Vale do Tejo	-5,33711	0
individual/collective	-1,5E+18	0
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	29,42304	0
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	18,4215	0
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	52,51137	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	34,89604	0
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	33,74669	0
field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	19,73143	0
field_description_ACTIVIDADES IMOBILIÁRIAS	25,82775	0
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	7,4181	0
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	12,62946	0

field_description_ALOJAMENTO, RESTAURAÇÃO SIMILARES	44,26436	0
field_description_CAPTAÇÃO, TRATAMENTO DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	14,01943	0
field_description_COMÉRCIO E VEÍCULOS	85,40046	0
field_description_CONSTRUÇÃO	32,86214	0
field_description_EDUCAÇÃO	24,43724	0
field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	6,99316	0
field_description_INDÚSTRIAS EXTRACTIVAS	7,4181	0
field_description_INDÚSTRIAS TRANSFORMADORAS	57,06631	0
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	19,08719	0
field_description_TRANSPORTES E ARMAZENAGEM	21,9879	0
field_description_individuals	-1,5E+18	0
field_description_not found	125,1038	0
Legal Form_Agrupamento Complementar de Empresas	2,47076	0,01349
Legal Form_Associação	17,55551	0
Legal Form_Autarquia	6,05507	0
Legal Form_Cooperativa	12,1316	0
Legal Form_Empresário em Nome Individual	2,47076	0,01349
Legal Form_Entidade Estrangeira	9,25655	0
Legal Form_Fundação	11,61284	0
Legal Form_Organismo de Administração Pública	6,05507	0
Legal Form_Sociedade Anónima	85,18258	0
Legal Form_Sociedade Unipessoal por Quotas	50,84022	0
Legal Form_Sociedade por Quotas	135,1748	0
Legal Form_individuals	-1,5E+18	0
Legal Form_unknown	126,5396	0

T-TEST: Cluster 0 VS Cluster 2	*statistic*	*pvalue*
gender_Feminino	-110,669	0
gender_Masculino	-45,9474	0
gender_company	6,83E+17	0
gender_other	-2,15633	0,03108
AMI_friend	-76,3643	0
consent_boolean	-5,78894	0
total_value	7,11267	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	-69,7666	0
registration_source_group_AUCHAN CAMPAIGN	-27,9922	0
registration_source_group_CHRISTMAS CAMPAIGNS	-12,5716	0
registration_source_group_CORPORATE PARTNERSHIPS	16,63064	0
registration_source_group_DONORS	-7,67463	0
registration_source_group_EMERGENCY CAMPAIGNS	0,11975	0,90468
registration_source_group_ENVIRONMENT	18,86661	0
registration_source_group_INTERNATIONAL CAMPAIGNS	8,85951	0
registration_source_group_NATIONAL CAMPAIGNS	-1,47759	0,13954
registration_source_group_OTHERS	78,33962	0
registration_source_group_SPONTANEOUS REGISTRATION	15,72508	0
registration_source_group_TMN CAMPAIGNS	3,82486	0,00013
registration_source_group_TRAINING	6,55274	0
1st_value	72,15897	0
avg_value_cont	-20,4625	0
avg_days_between_contrib	-50,4798	0
days_since_donor_last_contribution	-20,8749	0
everismonetary	-85,6798	0
total_contributions	-31,7696	0
region_Alentejo	6,50341	0
region_Algarve	1,05602	0,29098

region_Açores	2,78634	0,00534
region_Beira Interior	5,52118	0
region_Beira Litoral	-0,31446	0,75318
region_Entre-Douro-e-Minho	-6,09929	0
region_Lisboa	2,71943	0,00655
region_Madeira	3,91225	0,00009
region_NOT FOUND	17,30239	0
region_Trás-os-Montes e Alto Douro	1,73753	0,08232
region_Vale do Tejo	-10,4186	0
individual/collective	-6,9E+17	0
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	13,53269	0
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	8,4727	0
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	24,15183	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	16,04992	0
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	15,52129	0
field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	9,07518	0
field_description_ACTIVIDADES IMOBILIÁRIAS	11,8791	0
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	3,41185	0,00065
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	5,80874	0
field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES	20,35874	0
field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	6,44803	0
field_description_COMÉRCIO E VEÍCULOS	39,27869	0
field_description_CONSTRUÇÃO	15,11446	0
field_description_EDUCAÇÃO	11,23955	0

field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	3,2164	0,0013
field_description_INDÚSTRIAS EXTRACTIVAS	3,41185	0,00065
field_description_INDÚSTRIAS TRANSFORMADORAS	26,24681	0
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	8,77887	0
field_description_TRANSPORTES E ARMAZENAGEM	10,11301	0
field_description_individuals	-6,9E+17	0
field_description_not found	57,53967	0
Legal Form_Agrupamento Complementar de Empresas	1,13639	0,25582
Legal Form_Associação	8,0744	0
Legal Form_Autarquia	2,78494	0,00536
Legal Form_Cooperativa	5,57975	0
Legal Form_Empresário em Nome Individual	1,13639	0,25582
Legal Form_Entidade Estrangeira	4,25741	0,00002
Legal Form_Fundação	5,34115	0
Legal Form_Organismo de Administração Pública	2,78494	0,00536
Legal Form_Sociedade Anónima	39,17848	0
Legal Form_Sociedade Unipessoal por Quotas	23,38321	0
Legal Form_Sociedade por Quotas	62,17166	0
Legal Form_individuals	-6,9E+17	0
Legal Form_unknown	58,20002	0

T-TEST: Cluster 0 VS Cluster 3	*statistic*	*pvalue*
gender_Feminino	-83,7429	0
gender_Masculino	-60,6352	0
gender_company	1,28E+18	0
gender_other	-3,03872	0,00238
AMI_friend	-7,99039	0
consent_boolean	-3,60846	0,00031

total_value	32,89276	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	-10,2729	0
registration_source_group_AUCHAN CAMPAIGN	-12,234	0
registration_source_group_CHRISTMAS CAMPAIGNS	0,70229	0,4825
registration_source_group_CORPORATE PARTNERSHIPS	14,5002	0
registration_source_group_DONORS	5,97419	0
registration_source_group_EMERGENCY CAMPAIGNS	-2,70583	0,00682
registration_source_group_ENVIRONMENT	33,2853	0
registration_source_group_INTERNATIONAL CAMPAIGNS	1,96111	0,04988
registration_source_group_NATIONAL CAMPAIGNS	-5,30748	0
registration_source_group_OTHERS	48,27228	0
registration_source_group_SPONTANEOUS REGISTRATION	1,49289	0,13548
registration_source_group_TMN CAMPAIGNS	-46,0711	0
registration_source_group_TRAINING	2,06296	0,03913
1st_value	141,3907	0
avg_value_cont	-25,0227	0
avg_days_between_contrib	-29,1678	0
days_since_donor_last_contribution	-9,90513	0
everismonetary	-47,126	0
total_contributions	10,64753	0
region_Alentejo	-1,18746	0,23506
region_Algarve	-1,1656	0,24378
region_Açores	2,53397	0,01128
region_Beira Interior	-0,33972	0,73407
region_Beira Litoral	0,82436	0,40974
region_Entre-Douro-e-Minho	0,37469	0,70789
region_Lisboa	4,47068	0,00001
region_Madeira	-0,72238	0,47007
region_NOT FOUND	6,94774	0
region_Trás-os-Montes e Alto Douro	0,13137	0,89549

region_Vale do Tejo	-7,33717	0
individual/collective	-1,3E+18	0
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	26,01949	0
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	16,29057	0
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	46,43705	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	30,85939	0
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	29,843	0
field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	17,44898	0
field_description_ACTIVIDADES IMOBILIÁRIAS	22,8401	0
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	6,56	0
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	11,16853	0
field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES	39,14402	0
field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	12,39771	0
field_description_COMÉRCIO E VEÍCULOS	75,52166	0
field_description_CONSTRUÇÃO	29,06077	0
field_description_EDUCAÇÃO	21,61043	0
field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	6,18422	0
field_description_INDÚSTRIAS EXTRACTIVAS	6,56	0
field_description_INDÚSTRIAS TRANSFORMADORAS	50,46509	0
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	16,87925	0
field_description_TRANSPORTES E ARMAZENAGEM	19,44442	0
field_description_individuals	-1,3E+18	0
field_description_not found	110,6323	0
Legal Form_Agrupamento Complementar de Empresas	2,18495	0,0289

Legal Form_Associação	15,52475	0
Legal Form_Autarquia	5,35464	0
Legal Form_Cooperativa	10,72826	0
Legal Form_Empresário em Nome Individual	2,18495	0,0289
Legal Form_Entidade Estrangeira	8,18578	0
Legal Form_Fundação	10,26951	0
Legal Form_Organismo de Administração Pública	5,35464	0
Legal Form_Sociedade Anónima	75,32898	0
Legal Form_Sociedade Unipessoal por Quotas	44,95921	0
Legal Form_Sociedade por Quotas	119,5383	0
Legal Form_individuals	-1,3E+18	0
Legal Form_unknown	111,902	0

T-TEST: Cluster 1 VS Cluster 2	*statistic*	*pvalue*
gender_Feminino	-54,2038	0
gender_Masculino	54,21749	0
gender_company	0	1
gender_other	-0,45798	0,64697
AMI_friend	-205,366	0
consent_boolean	-12,998	0
total_value	-79,7395	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	-201,024	0
registration_source_group_AUCHAN CAMPAIGN	-70,6774	0
registration_source_group_CHRISTMAS CAMPAIGNS	-44,7362	0
registration_source_group_CORPORATE PARTNERSHIPS	0,47722	0,63321
registration_source_group_DONORS	-34,2072	0
registration_source_group_EMERGENCY CAMPAIGNS	-25,1784	0
registration_source_group_ENVIRONMENT	4,69533	0
registration_source_group_INTERNATIONAL CAMPAIGNS	2,05357	0,04002
registration_source_group_NATIONAL CAMPAIGNS	-5,03984	0

registration_source_group_OTHERS	307,8531	0
registration_source_group_SPONTANEOUS REGISTRATION	-21,1004	0
registration_source_group_TMN CAMPAIGNS	-25,8452	0
registration_source_group_TRAINING	-0,13572	0,89204
1st_value	-47,8683	0
avg_value_cont	-50,5081	0
avg_days_between_contrib	-124,72	0
days_since_donor_last_contribution	-234,332	0
everismonetary	-1359,17	0
total_contributions	-94,5557	0
region_Alentejo	7,05116	0
region_Algarve	0,86597	0,38651
region_Açores	-0,12674	0,89915
region_Beira Interior	3,04643	0,00232
region_Beira Litoral	-11,6579	0
region_Entre-Douro-e-Minho	-3,96126	0,00007
region_Lisboa	9,97505	0
region_Madeira	-1,94003	0,05238
region_NOT FOUND	14,88147	0
region_Trás-os-Montes e Alto Douro	-1,33655	0,18138
region_Vale do Tejo	-8,4793	0
individual/collective		
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	0	1
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	-176,378	0
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	-53,4602	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	176,3784	0
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	-25,8542	0
field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	0	1

field_description_ACTIVIDADES IMOBILIÁRIAS	-176,378	0
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	81,12737	0
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	-81,1274	0
field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES	-176,378	0
field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	-176,378	0
field_description_COMÉRCIO E VEÍCULOS	-25,8542	0
field_description_CONSTRUÇÃO	25,85424	0
field_description_EDUCAÇÃO		
field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	-39,5317	0
field_description_INDÚSTRIAS EXTRACTIVAS	81,12737	0
field_description_INDÚSTRIAS TRANSFORMADORAS	-81,1274	0
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	0	1
field_description_TRANSPORTES E ARMAZENAGEM	0	1
field_description_individuals		
field_description_not found	0	1
Legal Form_Agrupamento Complementar de Empresas	-81,1274	0
Legal Form_Associação	0	1
Legal Form_Autarquia	0	1
Legal Form_Cooperativa	59,70641	0
Legal Form_Empresário em Nome Individual	19,17306	0
Legal Form_Entidade Estrangeira	39,53172	0
Legal Form_Fundação		
Legal Form_Organismo de Administração Pública	0	1
Legal Form_Sociedade Anónima	0	1
Legal Form_Sociedade Unipessoal por Quotas		
Legal Form_Sociedade por Quotas	0	1

Legal Form_individuals		
Legal Form_unknown	59,70641	0

T-TEST: Cluster 1 VS Cluster 3	*statistic*	*pvalue*
gender_Feminino	-53,4961	0
gender_Masculino	53,75435	0
gender_company	0	1
gender_other	-3,59622	0,00032
AMI_friend	-41,516	0
consent_boolean	-7,86767	0
total_value	-53,4051	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	-55,7926	0
registration_source_group_AUCHAN CAMPAIGN	-33,3952	0
registration_source_group_CHRISTMAS CAMPAIGNS	-20,5055	0
registration_source_group_CORPORATE PARTNERSHIPS	-17,7399	0
registration_source_group_DONORS	-13,3442	0
registration_source_group_EMERGENCY CAMPAIGNS	-30,8926	0
registration_source_group_ENVIRONMENT	5,13447	0
registration_source_group_INTERNATIONAL CAMPAIGNS	-13,4238	0
registration_source_group_NATIONAL CAMPAIGNS	-14,7276	0
registration_source_group_OTHERS	272,8065	0
registration_source_group_SPONTANEOUS REGISTRATION	-60,7689	0
registration_source_group_TMN CAMPAIGNS	-133,007	0
registration_source_group_TRAINING	-11,4695	0
1st_value	-59,3529	0
avg_value_cont	-61,6362	0
avg_days_between_contrib	-72,0583	0
days_since_donor_last_contribution	-193,478	0
everismonetary	-317,546	0
total_contributions	-105,603	0

region_Alentejo	-3,92857	0,00009
region_Algarve	-3,04985	0,00229
region_Açores	-1,87888	0,06027
region_Beira Interior	-7,52527	0
region_Beira Litoral	-15,2425	0
region_Entre-Douro-e-Minho	7,79229	0
region_Lisboa	18,19211	0
region_Madeira	-12,8084	0
region_NOT FOUND	2,82785	0,00469
region_Trás-os-Montes e Alto Douro	-5,63474	0
region_Vale do Tejo	-3,88468	0,0001
individual/collective		
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	76,76889	0
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS		
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	-44,7884	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO		
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	0	1
field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	76,76889	0
field_description_ACTIVIDADES IMOBILIÁRIAS		
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	-76,7689	0
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	-155,978	0
field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES		
field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO		
field_description_COMÉRCIO E VEÍCULOS	-44,7884	0
field_description_CONSTRUÇÃO	0	1

field_description_EDUCAÇÃO		
field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	0	1
field_description_INDÚSTRIAS EXTRACTIVAS	-76,7689	0
field_description_INDÚSTRIAS TRANSFORMADORAS	-155,978	0
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	0	1
field_description_TRANSPORTES E ARMAZENAGEM	0	1
field_description_individuals		
field_description_not found	0	1
Legal Form_Agrupamento Complementar de Empresas	0	1
Legal Form_Associação	46,94736	0
Legal Form_Autarquia	0	1
Legal Form_Cooperativa	76,76889	0
Legal Form_Empresário em Nome Individual	0	1
Legal Form_Entidade Estrangeira	71,32745	0
Legal Form_Fundação		
Legal Form_Organismo de Administração Pública	0	1
Legal Form_Sociedade Anónima	0	1
Legal Form_Sociedade Unipessoal por Quotas		
Legal Form_Sociedade por Quotas	-76,7689	0
Legal Form_individuals		
Legal Form_unknown	-233,687	0

T-TEST: Cluster 2 VS Cluster 3	*statistic*	*pvalue*
gender_Feminino	18,8219	0
gender_Masculino	-18,7012	0
gender_company	0	1
gender_other	-1,60642	0,10819
AMI_friend	124,512	0
consent_boolean	4,9311	0

total_value	57,91092	0
registration_source_group_AMI RESOURCES/DEPARTMENTS	99,57734	0
registration_source_group_AUCHAN CAMPAIGN	32,84313	0
registration_source_group_CHRISTMAS CAMPAIGNS	22,60579	0
registration_source_group_CORPORATE PARTNERSHIPS	-8,66688	0
registration_source_group_DONORS	20,13625	0
registration_source_group_EMERGENCY CAMPAIGNS	-3,16249	0,00157
registration_source_group_ENVIRONMENT	-2,66593	0,00768
registration_source_group_INTERNATIONAL CAMPAIGNS	-7,92277	0
registration_source_group_NATIONAL CAMPAIGNS	-4,33393	0,00001
registration_source_group_OTHERS	-37,6302	0
registration_source_group_SPONTANEOUS REGISTRATION	-17,8279	0
registration_source_group_TMN CAMPAIGNS	-54,8472	0
registration_source_group_TRAINING	-5,42686	0
1st_value	25,40449	0
avg_value_cont	26,38235	0
avg_days_between_contrib	58,30931	0
days_since_donor_last_contribution	17,4458	0
everismonetary	42,36033	0
total_contributions	73,67835	0
region_Alentejo	-8,96019	0
region_Algarve	-2,64634	0,00814
region_Açores	-1,0116	0,31174
region_Beira Interior	-6,98471	0
region_Beira Litoral	1,34052	0,18009
region_Entre-Douro-e-Minho	8,8417	0
region_Lisboa	1,22822	0,21938
region_Madeira	-5,52297	0
region_NOT FOUND	-13,5495	0
region_Trás-os-Montes e Alto Douro	-2,09639	0,03606

region_Vale do Tejo	5,81238	0
individual/collective		
field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	39,25762	0
field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	155,9757	0
field_description_ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	39,25762	0
field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	-155,976	0
field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	25,54988	0
field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	39,25762	0
field_description_ACTIVIDADES IMOBILIÁRIAS	155,9757	0
field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	-81,1269	0
field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA		
field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES	155,9757	0
field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	155,9757	0
field_description_COMÉRCIO E VEÍCULOS	0	1
field_description_CONSTRUÇÃO	-25,5499	0
field_description_EDUCAÇÃO		
field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	39,25762	0
field_description_INDÚSTRIAS EXTRACTIVAS	-81,1269	0
field_description_INDÚSTRIAS TRANSFORMADORAS		
field_description_OUTRAS ACTIVIDADES DE SERVIÇOS	0	1
field_description_TRANSPORTES E ARMAZENAGEM	0	1
field_description_individuals		
field_description_not found	0	1
Legal Form_Agrupamento Complementar de Empresas	81,1269	0

Legal Form_Associação	25,54988	0
Legal Form_Autarquia	0	1
Legal Form_Cooperativa	0	1
Legal Form_Empresário em Nome Individual	-18,895	0
Legal Form_Entidade Estrangeira	0	1
Legal Form_Fundação		
Legal Form_Organismo de Administração Pública	0	1
Legal Form_Sociedade Anónima	0	1
Legal Form_Sociedade Unipessoal por Quotas		
Legal Form_Sociedade por Quotas	-39,2576	0
Legal Form_individuals		
Legal Form_unknown	-168,668	0

6. SEGMENTATION MODEL RESULTS

Cluster 0

	Rel. Freq. of Donors in each Region
Vale do Tejo	0,34
Entre-Douro-e-Minho	0,25
Lisboa	0,18
Beira Litoral	0,12
Algarve	0,03
Alentejo	0,02
Beira Interior	0,02
Madeira	0,01
NOT FOUND	0,01
Açores	0,01
Trás-os-Montes e Alto Douro	0,01

	Rel. Freq. of Donors per Gender
Feminino	0,71
Masculino	0,29
other	0

	Rel Freq. of Donors Registered as AMI_friend
1	0,57
0	0,43

	Rel Freq. of Donors per Registration Source Group
AMI RESOURCES/DEPARTMENTS	0,56
AUCHAN CAMPAIGN	0,14
SPONTANEOUS REGISTRATION	0,11
CHRISTMAS CAMPAIGNS	0,06
TMN CAMPAIGNS	0,04
DONORS	0,04
EMERGENCY CAMPAIGNS	0,03
NATIONAL CAMPAIGNS	0,01
OTHERS	0,01
INTERNATIONAL CAMPAIGNS	0
CORPORATE PARTNERSHIPS	0
TRAINING	0
ENVIRONMENT	0

	Rel Freq. of Donors per Company Field Description
Individuals	1

	Rel Freq. of Donors per Legal From
individuals	1

Avg Total Value Donate Per Donor	Avg Total Number of Contributions Per Donor	Avg Number of Days Since Donor Last Contribution (Recency)	Median Number of Days Between Contribution (Frequency)
801,34	15,37	2505	127,67

Cluster 1

	Rel Freq. of Donors per Region
Vale do Tejo	0,25
Entre-Douro-e-Minho	0,21
Lisboa	0,19
Beira Litoral	0,12
NOT FOUND	0,07
Alentejo	0,04
Algarve	0,03
Beira Interior	0,03
Madeira	0,02
Açores	0,02
Trás-os-Montes e Alto Douro	0,02

	Rel Freq. of Donors per Gender
company	1

	Rel Freq. of Donors Registered as AMI_friend
0	0,97
1	0,03

	Rel Freq. of Donors per Registration Source Group
OTHERS	0,5
SPONTANEOUS REGISTRATION	0,21
TMN CAMPAIGNS	0,05
ENVIRONMENT	0,05

AMI RESOURCES/DEPARTMENTS	0,05
CORPORATE PARTNERSHIPS	0,04
EMERGENCY CAMPAIGNS	0,03
INTERNATIONAL CAMPAIGNS	0,02
CHRISTMAS CAMPAIGNS	0,01
DONORS	0,01
NATIONAL CAMPAIGNS	0,01
TRAINING	0,01
AUCHAN CAMPAIGN	0

	Rel Freq. of Donors per Company Field Description
not found	0,33
COMÉRCIO E VEÍCULOS	0,19
INDÚSTRIAS TRANSFORMADORAS	0,09
ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	0,08
ALOJAMENTO, RESTAURAÇÃO E SIMILARES	0,06
ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	0,04
ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	0,04
CONSTRUÇÃO	0,03
ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	0,03
ACTIVIDADES IMOBILIÁRIAS	0,02
EDUCAÇÃO	0,02
TRANSPORTES E ARMAZENAGEM	0,02
ACTIVIDADES FINANCEIRAS E DE SEGUROS	0,01
OUTRAS ACTIVIDADES DE SERVIÇOS	0,01
ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	0,01

CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	0,01
AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	0,01
INDÚSTRIAS EXTRACTIVAS	0
ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	0
ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	0

Avg Total Value Donate Per Donor	*Avg Total Number of Contributions Per Donor*	*Avg Number of Days Since Donor Last Contribution (Recency)*	*Median Number of Days Between Contribution (Frequency)*
1358,32	2,31	1764,72	-1

Cluster 2

	Rel Freq. of Donors per Region
Vale do Tejo	0,3
Entre-Douro-e-Minho	0,21
Lisboa	0,17
Beira Litoral	0,11
NOT FOUND	0,05
Alentejo	0,05
Algarve	0,03
Beira Interior	0,03
Madeira	0,03
Trás-os-Montes e Alto Douro	0,02
Açores	0,01

	Rel Freq. of Donors per Gender
Feminino	0,58
Masculino	0,42
other	0

	Rel Freq. of Donors Registered as AMI_friend
0	0,95
1	0,05

	Rel Freq. of Donors per Registration Source Group
TMN CAMPAIGNS	0,37
SPONTANEOUS REGISTRATION	0,2
OTHERS	0,2
AMI RESOURCES/DEPARTMENTS	0,09
AUCHAN CAMPAIGN	0,04
EMERGENCY CAMPAIGNS	0,03
NATIONAL CAMPAIGNS	0,02
CHRISTMAS CAMPAIGNS	0,01
CORPORATE PARTNERSHIPS	0,01
INTERNATIONAL CAMPAIGNS	0,01
DONORS	0,01
TRAINING	0,01
ENVIRONMENT	0

	Rel Freq. of Donors per Company Field Description
individuals	1

Avg Total Value Donate Per Donor	*Avg Total Number of Contributions Per Donor*	*Avg Number of Days Since Donor Last Contribution (Recency)*	*Median Number of Days Between Contribution (Frequency)*

101	1,62	2046,48	-1

Cluster 3

	Rel Freq. of Donors per Region
Vale do Tejo	0,29
Entre-Douro-e-Minho	0,23
Lisboa	0,23
Beira Litoral	0,07
NOT FOUND	0,05
Alentejo	0,04
Algarve	0,03
Beira Interior	0,02
Açores	0,01
Madeira	0,01
Trás-os-Montes e Alto Douro	0,01

	Rel Freq. of Donors per Gender
Masculino	0,64
Feminino	0,36
other	0

	AMI_friend
0	1
1	0

	Rel Freq. of Donors per Registration Source Group
OTHERS	0,94
SPONTANEOUS REGISTRATION	0,04

NATIONAL CAMPAIGNS	0,01
TMN CAMPAIGNS	0
ENVIRONMENT	0
INTERNATIONAL CAMPAIGNS	0
CORPORATE PARTNERSHIPS	0
EMERGENCY CAMPAIGNS	0
AUCHAN CAMPAIGN	0
TRAINING	0
CHRISTMAS CAMPAIGNS	0
DONORS	0

	Rel Freq. of Donors per Field Description
individuals	1

Avg Total Value Donate Per Donor	*Avg Total Number of Contributions Per Donor*	*Avg Number of Days Since Donor Last Contribution (Recency)*	*Median Number of Days Between Contribution (Frequency)*
0,12	0,01	3,73	-1

7. FEATURES SELECTED DESCRIPTION

Context	Feature Name	Description
Demographics	gender_Feminino	Donor's gender is Female
	gender_Masculino	Donor's gender is Male
	gender_company	Company (gender not applicable)
	gender_other	Gender not defined
	region_Alentejo	Donor comes from Alentejo
	region_Algarve	Donor comes from Algarve
	region_Açores	Donor comes from Açores
	region_ Beira Interior	Donor comes from Beira Interior
	region_ Beira Litoral	Donor comes from Beira Litoral
	region_Entre-Douro-e-Minho	Donor comes from Entre-Douro-e-Minho
	region_Lisboa	Donor comes from Lisboa
	region_Madeira	Donor comes from Madeira
	region_Trás-os-Montes e Alto Douro	Donor comes from Trás-os-Montes e Alto Douro
	region_Vale do Tejo	Donor comes from Vale do Tejo
	field_description_ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	Company's work field is related to administrative work and support
	field_description_ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	Company's work field is related to arts and sports
	field_description_ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	Company's work field is related to communication
	field_description_ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	Company's work field is related to social work and health
	field_description_ACTIVIDADES FINANCEIRAS E DE SEGUROS	Company's work field is related to financial services

Firmographics	field_description_ACTIVIDADES IMOBILIÁRIAS	Company's work field is related to real estate
	field_description_ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	Company's work field is related to public administration and safety
	field_description_AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	Company's work field is related to primary sector activities
	field_description_ALOJAMENTO, RESTAURAÇÃO E SIMILARES	Company's work field is related to restaurants
	field_description_CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	Company's work field is related to water and waste treatment
	field_description_COMÉRCIO E VEÍCULOS	Company's work field is related to vehicles
	field_description_CONSTRUÇÃO	Company's work field is related to construction
	field_description_EDUCAÇÃO	Company's work field is related to education
	field_description_ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	Company's work field is related to water, electricity and gas
	field_description_INDÚSTRIAS EXTRACTIVAS	Company's work field is related to extractive industries
	field_description_INDÚSTRIAS TRANSFORMADORAS	Company's work field is related to manufacturing industries
	field_description_OUTRAS ACTIVIDADES SERVIÇOS	Company's work field is not defined (others)
	field_description_TRANSPORTES E ARMAZENAGEM	Company's work field is related to transports and storage
	field_description_individuals	Donor is an individual (work field not applicable)
	Legal Form_Agrupamento Complementar Empresas	Company's legal form is Complementary Company

	Legal Form_Associação	Company's legal form is Association
	Legal Form_Autarquia	Company's legal form is autarchy
	Legal Form_Cooperativa	Company's legal form is Collective company
	Legal Form_Empresário em Nome Individual	Company's legal form is Sole proprietorship
	Legal Form_Entidade Estrangeira	Company's legal form is Foreign entity
	Legal Form_Fundação	Company's legal form is Foundation
	Legal Form_Organismo de Administração Pública	Company's legal form is Public Administration
	Legal Form_Sociedade Anónima	Company's legal form is Public limited company
	Legal Form_Sociedade Unipessoal por Quotas	Company's legal form is Private Limited Company
	Legal Form_individuals	Donor is an individual (legal form not applicable)
	Legal Form_unknown	Not defined or unknown legal form
Relation with AMI	AMI_friend	Donor is registered as AMI Friend
	consent_boolean	Donor gave consent to be contacted by AMI
	registration_source_AMI RESOURCES/DEPARTMENTS	Donor registered with AMI through channels with direct contact with departments
	registration_source_AUCHAN CAMPAIGN	Donor registered with AMI through an Auchan campaign
	registration_source_CHRISTMAS CAMPAIGNS	Donor registered with AMI through a Christmas campaign
	registration_source_CORPORATE PARTNERSHIPS	Donor registered with AMI through a corporate partnership
	registration_source_DONORS	Donor registered with AMI through a donation
	registration_source_EMERGENCY CAMPAIGNS	Donor registered with AMI through a subscription to an Emergency campaign
	registration_source_ENVIRONMENT	Donor registered with AMI through a campaign related to the Environment
	registration_source_INTERNATIONAL CAMPAIGNS	Donor registered with AMI through an application related to an International Campaign

	registration_source_NATIONAL CAMPAIGNS	Donor registered with AMI through an application related to a National Campaign
	registration_source_SPONTANEOUS REGISTRATION	Donor registered with AMI through an spontaneous registration
	registration_source_TMN CAMPAIGNS	Donor registered with AMI through a TMN Campaign
	registration_source_TRAINING	Donor registered with AMI through a campaign related to a Training
Contributions details	total_value	Total value every contributed to AMI by the donor
	1st_value	Value of first contribution the donor ever made to AMI
	avg_value_cont	Average value of donor's contributions
	total_contributions	Total number of contributions ever made to AMI by the donor
	everismonetary	If the donor ever made a monetary contribution
	avg_days_between_contrib	Average number of days between contributions by the donor (frequency)
	days_since_donor_last_contribution	Number of days since the donor's last contribution (recency)

8. SMOTE RESAMPLING

This algorithm is called Synthetic Minority Over-sampling Technique and it was design to generate samples that are coherent with the minor class distribution. SMOTE considers the existing relationships between samples and then creates synthetics points that connect neighbors.

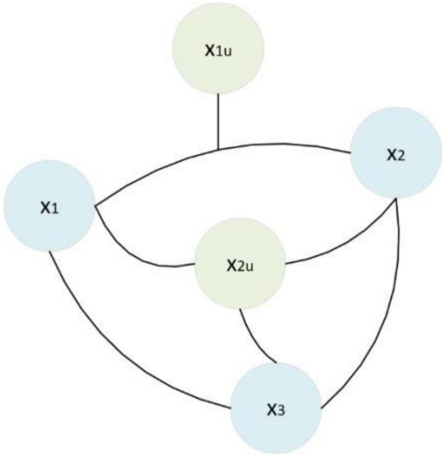

Figure 1 - neighborhood containing three points (x1, x2, x3) and two synthetic ones (O'Reilly)

As we can see from the figure above, SMOTE upsamples the classes by generating the synthetic samples x_{1u} and x_{2u}. This procedure is based on the assumption that properties of the samples are not different within a certain neighborhood radius, allowing the creation os synthetic points that follow the same original distribution.

9. GRID SEARCH: Hyperparameter Tuning

To customize a machine learning model to a specific dataset and met necessary needs, it is necessary to previously set hyperparameters. An hyperparamenter is a model characteristic that is external to the model and it can not be calculated from data. The best approach to define hyperparameters starts by testing different values for model hyperparameters and eventually choose the one that achieves the best performance (Brownlee, 2020). Grid Search is a technique used to perform an exhaustive search over hyperparameter values for an estimator (Scikit-learn.org, 2019). The output of this technique is the optimal combination of one or multiple hyperparameters that ensure the best performance of the model.

10. LOGISTIC REGRESSION

Logistic Regression (LR) is frequently used for classification problems. It entails approximately the same assumptions as linear regression, since it also attempts to find a relationship between a dependent variable and one or more independent features. However, it allows to retrieve binary results (Hosmer et. all 2013). In LR input features are linearly scaled and the result is fed to the logistic function. The logistic function transforms the input in nonlinear and the output represents the probability, within an interval [0,1], of the input belonging to class 1 (H0). The regression uses the logistic function (Sigmoid Function) to find the solution to this hypothesis:

$$H_\theta(x) = P(y = 1|x) = \sigma(\theta^T x) = \frac{1}{1 + e^{(-\theta^T x)}}$$

. The loss function of logistic regression (Logistic Loss) aims to measure the difference between the actual output and the one given by the model : the error or loss (Luo 2019). The cost function will sum the errors made for all training data with m samples, following the formula below:

$$J(\theta) = \frac{1}{m}[\sum_{i=1}^{m} -y^{(i)} log(h_\theta(x^{(i)})) + (1 - y^{(i)}) log(1 - h_\theta(x^{(i)}))]$$

The goal is to minimize this Loss Function, through a set of iterations, in order to minimize the errors made by the model, using a gradient descent function.

11. XG-Boost

XGBoost, short for Extreme Gradient Boosting, is an ensemble method - it combines multiple machine learning models (the base learners) to enhance the results when compared to their individual performance - with a gradient boosting framework (Wade & Glynn, 2020). Decision Trees are the most common baseline models for the case and make predictions by splitting data into branches and following them until the leave level. XGBoost conglomerates trees through boosting: the model will consecutively learn from the errors made by each individual tree and adapt the future predictions, so these mistakes are not repeated. (Wade & Glynn, 2020) More specifically, gradient boosting, involves the optimization of a loss function, a weak learner (decision trees), and an additive model (adds tree each time) - which will join all the weak learners until minimizing the loss function (Brownlee, 2016). The loss function considers the residuals, which indicate how different the model's predictions are from reality. Minimizing the square of these residuals is the objective of a linear regression model (Wade & Glynn, 2020).

XGBoost presents multiple advantages when compared to other classification models, including speed - thanks to block compression (blocks are compressed and decompressed when loading into main memory, which is faster than disk reading) and sharding (data is split into multiple disks, to increase performance) for instance - and accuracy - due to the possibility of regularization, and, as mentioned before, because it is an ensemble model and presents the inherent benefits.

Avg Total Value Donate Per Donor	Avg Total Number of Contributions Per Donor	Avg Number of Days Since Donor Last Contribution (Recency)	Median Number of Days Between Contribution (Frequency)	Avg Purchasing Power	Avg Number of People per Household	Avg Education Score
111	1,72	2118,04	-1	120,28	1,78	2,85

0	0,94
1	0,06

	Rel Freq. of Donors ***per Registration Source Groups***
TMN CAMPAIGNS	0,38
OTHERS	0,2
SPONTANEOUS REGISTRATION	0,18
AMI RESOURCES/DEPARTMENTS	0,09
AUCHAN CAMPAIGN	0,04
EMERGENCY CAMPAIGNS	0,03
NATIONAL CAMPAIGNS	0,02
CHRISTMAS CAMPAIGNS	0,01
CORPORATE PARTNERSHIPS	0,01
INTERNATIONAL CAMPAIGNS	0,01
DONORS	0,01
TRAINING	0,01
ENVIRONMENT	0

	Rel Freq. of Donors ***per Company Field Description***
individuals	1

12. PORDATA DATA

Municipality	Total Population	No Schooling	1st-4-th grade	5th-6th grade	7th - 9th grade	High school	Medium	Superior	Purchasing Powe (2017)	Average number of people per household (2020)
Arcos de Valdevez	20 268	5 060	6 972	1 998	2 801	2 038	93	1 306	67,8	1,2
Caminha	14 650	1 641	4 382	1 813	2 766	2 284	134	1 630	78,9	1,1
Melgaço	8 392	1 892	3 135	836	1 047	887	77	518	62,0	1,1
Monção	17 149	3 163	5 585	2 166	2 359	2 292	166	1 418	70,2	1,3
Paredes de Coura	8 071	1 690	2 611	1 049	1 325	923	65	408	66,4	1,4
Ponte da Barca	10 522	1 989	3 503	1 227	1 747	1 282	78	696	64,4	1,4
Ponte de Lima	36 762	5 406	10 761	6 088	7 269	4 399	243	2 596	71,0	1,8
Valença	12 256	1 454	4 150	1 762	2 248	1 698	108	836	82,7	1,6
Viana do Castelo	76 229	7 975	19 882	10 883	14 608	11 702	607	10 572	93,1	1,7
Vila Nova de Cerveira	8 023	1 161	2 344	1 078	1 543	1 130	82	685	84,2	1,4
Amares	15 750	1 847	4 714	2 380	3 007	2 316	156	1 330	70,9	1,8
Barcelos	10	9 333	30 188	20 688	20 058	12 261	688	7 173	78,9	2,4

Maia	112 530	6 634	27 601	12 891	22 026	20 416	⊥ 1 435	21 527	110,7	2,3
Matosinhos	150 366	11 185	40 246	18 208	27 428	24 602	⊥ 1 677	27 020	123,0	2,1
Oliveira de Azeméis	58 932	5 420	18 867	10 614	11 371	7 358	⊥ 502	4 800	83,1	2,2
Paredes	70 716	6 763	23 256	13 611	13 444	8 205	⊥ 474	4 963	79,8	2,4
Porto	209 212	13 814	50 642	21 333	35 585	32 936	⊥ 1 917	52 985	157,8	1,5
Póvoa de Varzim	52 991	4 357	15 051	9 383	9 972	7 441	⊥ 417	6 370	95,5	1,7
Santa Maria da Feira	117 270	10 799	35 941	19 825	21 968	15 581	⊥ 980	12 176	84,8	2,2
Santo Tirso	61 648	5 920	21 374	9 750	11 039	7 599	⊥ 492	5 474	85,8	2,2
São João da Madeira	18 587	1 285	5 089	2 697	3 787	3 037	⊥ 210	2 482	135,4	2,1
Trofa	32 924	2 644	10 209	5 425	6 656	4 714	⊥ 361	2 915	92,7	2,4
Vale de Cambra	19 965	2 458	6 491	3 079	3 349	2 505	⊥ 195	1 888	86,9	1,8
Valongo	7 [illegible]	5 562	21 977	11 843	15 730	1 [illegible]	⊥ 852 083	9 [illegible]	91,7	2,4

Alijó	10 596	1 868	4 161	1 370	1 455	1 082	62	598	63,6	1,2
Armamar	5 468	875	2 105	746	811	611	32	288	63,3	1,1
Carrazeda de Ansiães	5 737	1 195	2 318	592	687	533	31	381	63,0	1,1
Freixo de Espada à Cinta	3 351	759	1 273	398	454	279	21	167	63,2	1,0
Lamego	22 973	3 373	6 674	3 120	3 938	3 060	130	2 678	81,4	1,5
Mesão Frio	3 854	687	1 385	531	606	444	22	179	69,5	1,6
Moimenta da Beira	8 754	1 412	3 043	1 056	1 381	1 084	63	715	66,3	1,2
Murça	5 287	1 058	1 867	682	760	520	31	369	61,2	1,3
Penedono	2 590	489	953	351	315	283	15	184	62,1	1,0
Peso da Régua	14 809	2 184	4 804	1 892	2 545	1 961	84	1 339	82,5	1,7
Sabrosa	5 571	1 048	2 086	660	847	567	22	341	61,9	1,3
Santa Marta de Penaguião	6 470	1 406	2 326	800	875	633	30	400	58,7	1,4
São João da Pesqueira	6 815	1 236	2 503	1 032	1 005	671	31	337	64,6	1,3
Sernancelhe	4 954	854	1 846	601	744	618	35	256	58,8	1,2
Tabuaço	5 560	964	1 973	775	923	610	24	291	55,3	1,4
Tarouca	6 770	990	2 374	1 014	1 139	784	35	434	63,4	1,1
Torre de Moncorvo	7 826	1 641	2 876	790	1 003	886	58	572	62,3	1,0
Vila Nova de Foz Côa	6 520	1 204	2 498	678	844	747	45	504	68,0	1,0
Vila Real	44 136	4 46	11 129	4 584	7 823	7 426	312	8 394	98,1	1,6

		8								
Alfândega da Fé	4 608	930	1 624	487	729	488	31	319	66,0	1,2
Bragança	30 964	4 022	7 999	3 157	5 137	4749	338	5 562	96,5	1,3
Macedo de Cavaleiros	13 928	2 323	4 808	1 473	2 163	1616	91	1 454	73,5	1,2
Miranda do Douro	6 752	1 322	2 167	676	1 090	838	48	611	72,7	1,2
Mirandela	20 954	3 292	6 334	2 592	3 273	2861	139	2 463	83,0	1,4
Mogadouro	8 655	1 830	2 916	913	1 267	912	73	744	67,9	1,1
Vila Flor	5 976	1 068	2 188	725	887	647	32	429	62,4	1,1
Vimioso	4 264	991	1 628	475	546	362	19	243	62,3	0,8
Vinhais	8 372	1 779	3 338	1 189	876	731	44	415	57,9	1,1
Alcobaça	48 411	5 701	14 968	6 075	9 487	7184	437	4 559	86,7	1,5
Alenquer	36 130	4 111	9 935	4 823	7 417	6173	342	3 329	89,2	1,9
Arruda dos Vinhos	10 929	1 039	2 909	1 366	2 003	1957	141	1 514	91,0	2,3

Bombarral	11 425	1 458	3 663	1 570	2 115	1 550	104	965	83,5	1,5
Cadaval	12 206	1 823	4 128	1 609	2 072	1 671	99	804	70,8	1,5
Caldas da Rainha	44 190	4 697	11 760	4 907	9 132	7 513	500	5 681	98,1	1,6
Lourinhã	21 767	2 945	6 415	3 060	4 047	3 179	215	1 906	78,3	1,5
Nazaré	13 052	1 406	4 073	1 805	2 427	1 913	152	1 276	85,6	1,0
Óbidos	10 049	1 370	3 070	1 339	1 800	1 457	89	924	75,5	1,3
Peniche	23 634	2 850	7 204	3 465	4 631	3 158	232	2 094	85,9	1,2
Sobral de Monte Agraço	8 466	951	2 447	1 212	1 612	1 324	89	831	103,4	2,0
Torres Vedras	67 324	7 616	18 649	9 056	13 580	10 130	669	7 624	95,3	1,7
Águeda	41 087	4 116	12 548	6 537	7 883	5 589	418	3 996	86,5	2,0
Albergaria-a-Velha	21 359	2 092	6 203	3 770	4 253	2 783	225	2 033	84,5	1,9
Anadia	25 411	3 342	8 197	3 272	4 226	3 287	266	2 821	78,7	1,8
Aveiro	67 019	4 769	15 037	8 228	13 423	10 510	651	14 401	123,1	1,9
Estarreja	23 05	2 402	7 246	3 594	4 637	2 878	151	2 146	82,1	2,0

	4									
Ílhavo	32 643	2 602	9 022	4 449	6 551	4761	310	4 948	88,6	1,7
Murtosa	8 946	1 199	3 198	1 487	1 411	880	51	720	69,3	1,3
Oliveira do Bairro	19 401	2 341	5 575	2 970	3 501	2628	189	2 197	79,7	2,1
Ovar	46 815	3 949	13 114	7 139	9 496	7022	388	5 707	88,9	1,9
Sever do Vouga	10 716	1 212	3 377	1 728	1 996	1381	95	927	74,0	1,6
Vagos	19 446	2 666	5 850	2 936	3 561	2486	162	1 785	72,1	1,7
Arganil	10 795	1 952	3 811	1 193	1 967	1249	54	569	68,2	1,0
Cantanhede	31 872	4 846	10 106	3 782	5 284	4096	287	3 471	79,8	1,7
Coimbra	125 559	9 331	26 950	11 196	21 811	21230	1 235	33 806	128,7	1,7
Condeixa-a-Nova	14 340	1 705	3 676	1 307	2 580	2438	160	2 474	77,9	2,0
Figueira da Foz	54 060	6 642	14 323	6 071	10 593	8623	457	7 351	95,0	1,3
Góis	3 793	830	1 335	368	660	393	25	182	64,0	0,7
Lousã	14 824	1 314	4 161	1 839	3 179	2466	145	1 720	80,6	1,6
Mealhada	17	1	5 251	2 175	3 301	26	233	2	86,9	1,9

	597	807				44		186		
Mira	10 905	1 664	3 489	1 348	1 683	1 340	⊥ 120	1 261	72,2	1,3
Miranda do Corvo	11 269	1 366	3 524	1 494	2 175	1 640	⊥ 87	983	67,3	1,7
Montemor-o-Velho	22 789	3 265	6 505	2 776	4 256	3 402	⊥ 171	2 414	71,0	1,9
Mortágua	8 595	1 437	3 154	1 062	1 271	934	⊥ 54	683	74,1	1,4
Oliveira do Hospital	18 068	2 695	6 335	2 341	3 124	2 123	⊥ 127	1 323	74,5	1,4

Pampilhosa da Serra	4 160	1 213	1 617	385	470	350	10	115	64,6	0,7
Penacova	13 377	2 163	4 791	1 698	2 342	1 437	85	861	63,7	1,6
Penela	5 252	916	1 856	523	857	632	53	415	70,0	1,1
Soure	16 987	3 205	5 060	1 539	3 112	2 579	160	1 332	70,7	1,4
Tábua	10 434	1 575	3 760	1 233	1 945	1 201	81	639	68,6	1,3
Vila Nova de Poiares	6 185	803	1 914	797	1 354	867	49	401	70,5	1,5
Alvaiázere	6 500	1 364	2 369	697	911	708	51	400	66,5	1,1
Ansião	11 445	2 027	3 736	1 263	1 901	1 566	136	816	73,5	1,4
Batalha	13 335	1 478	3 997	1 742	2 599	2 013	174	1 332	84,8	1,9
Castanheira de Pêra	2 853	518	1 133	288	454	294	20	146	65,6	0,9
Figueiró dos Vinhos	5 512	1 037	1 934	626	860	634	56	365	65,5	1,1
Leiria	107 580	10 931	26 728	13 224	21 749	17 851	1 301	15 796	103,4	1,8
Marinha Grande	32 879	3 198	8 708	3 972	7 173	5 809	369	3 650	98,5	1,7
Pedrógão Grande	3 481	697	1 260	392	490	392	61	189	67,9	0,9
Pombal	47 489	8 928	14 253	5 282	8 332	6 453	458	3 783	82,2	1,5
Porto de Mós	20 684	2 569	6 507	2 754	3 999	2 801	222	1 832	80,2	1,8
Aguiar da Beira	4 862	1 236	1 743	455	655	514	33	226	67,4	0,9
Carregal do Sal	8 488	1 317	2 934	1 170	1 477	993	39	558	70,9	1,4

Castro Daire	13 308	2 765	4 786	1 739	2 005	1 262	49	702	64,8	1,1
Mangualde	17 207	2 272	5 717	2 312	3 109	2 135	94	1 568	82,4	1,4
Nelas	12 111	1 529	4 141	1 463	2 194	1 601	77	1 106	77,1	1,5
Oliveira de Frades	8 718	1 041	2 815	1 355	1 585	1 132	82	708	77,5	1,7
Penalva do Castelo	6 977	1 509	2 572	873	956	640	39	388	58,4	1,3
Santa Comba Dão	10 064	1 432	3 306	1 415	1 730	1 255	93	833	71,5	1,5
São Pedro do Sul	14 706	2 341	5 117	2 026	2 227	1 779	109	1 107	68,7	1,3
Sátão	10 717	1 913	3 548	1 475	1 605	1 249	78	849	61,9	1,2
Tondela	25 503	3 832	8 966	3 323	4 134	3 073	151	2 024	75,0	1,5
Vila Nova de Paiva	4 476	888	1 378	639	726	518	22	305	62,7	1,0
Viseu	84 115	8 360	21 578	9 538	15 184	13 792	682	14 981	94,4	1,7
Vouzela	9 232	1 360	3 392	1 261	1 453	1 038	68	660	64,0	1,4
Castelo Branco	49 002	6 030	13 389	4 514	9 045	8 265	449	7 310	95,8	1,3

Idanha-a-Nova	8 870	2 491	3 249	751	1 155	747	29	448	67,6	0,7
Oleiros	5 327	1 381	2 137	433	618	432	40	286	63,6	1,0
Penamacor	5 267	1 451	1 915	529	683	456	17	216	60,6	0,7
Proença-a-Nova	7 511	1 451	2 650	677	1 165	937	61	570	69,0	1,1
Vila Velha de Ródão	3 258	616	1 423	288	440	309	7	175	71,7	0,9
Abrantes	34 378	4 396	10 675	3 954	6 642	4 933	253	3 525	89,2	1,4
Alcanena	12 005	1 342	3 814	1 669	2 201	1 807	96	1 076	86,1	1,6
Constância	3 437	404	1 025	387	677	556	36	352	83,1	1,8
Entroncamento	16 951	1 002	3 620	1 749	3 764	3 615	219	2 982	98,5	2,0
Ferreira do Zêzere	7 525	1 453	2 632	876	1 228	892	63	381	67,8	1,0
Mação	6 672	1 346	2 358	687	1 202	653	38	388	68,8	0,9
Ourém	39 265	5 947	11 214	5 102	7 213	5 559	437	3 793	83,6	1,5
Sardoal	3 458	451	1 115	419	665	498	22	288	68,6	1,2
Sertã	13 900	2 592	4 722	1 369	2 438	1 785	169	825	72,6	1,2
Tomar	35 415	4 049	10 698	4 109	6 629	5 456	318	4 156	85,0	1,4
Torres Novas	31 654	3 412	8 944	3 800	5 954	5 155	296	4 093	96,8	1,7
Vila de Rei	3 088	686	1 185	246	455	328	48	140	66,2	1,1
Vila Nova da Barquinha	6 320	626	1 885	831	1 204	1 061	69	644	72,3	1,8
Almeida	6 650	1	2 591	608	1 005	79	37	465	74,2	0,9

		150				4				
Belmonte	6 051	988	2 069	704	954	796	53	487	71,3	1,3
Celorico da Beira	6 755	1 312	2 482	598	1 127	722	51	463	65,0	1,1
Covilhã	45 428	5 682	13 591	4 863	8 242	6817	412	5 821	86,6	1,3
Figueira de Castelo Rodrigo	5 588	1 150	2 014	652	797	528	32	415	66,8	1,0
Fornos de Algodres	4 447	866	1 786	415	631	423	31	295	58,8	1,1
Fundão	25 779	4 506	8 022	2 813	4 640	3099	249	2 450	77,9	1,2
Gouveia	12 557	2 126	4 818	1 294	1 857	1279	77	1 106	65,9	1,1
Guarda	36 708	3 848	9 423	3 333	7 689	5812	373	6 230	96,2	1,4
Manteigas	3 087	436	1 288	311	435	368	25	224	63,9	1,1
Mêda	4 680	1 017	1 836	474	580	426	32	315	62,1	0,9
Pinhel	8 627	1 642	3 243	828	1 351	941	51	571	62,8	1,0
Sabugal	11 540	2 783	4 415	895	1 605	1092	80	670	63,4	0,7
Seia	21 941	3 096	8 118	2 332	3 539	2768	166	1 922	76,2	1,2
Trancoso	8 773	1 620	3 218	754	1 429	1002	59	691	66,7	1,1
Alcochete	14 237	1 090	2 920	1 501	2 803	2926	172	2 825	118,8	2,2

Almada	148 447	11 069	35 248	16 036	31 068	28068	⊥ 1 701	25 257	108,7	1,6
Amadora	149 233	11 752	37 290	16 934	30 929	28390	⊥ 1 677	22 261	100,6	2,1
Barreiro	67 543	5 249	18 670	7 477	14 327	12494	⊥ 685	8 641	100,0	1,8
Cascais	173 824	9 767	30 426	15 484	34 083	37171	⊥ 2 709	44 184	122,1	1,9
Lisboa	477 239	32 413	96 850	38 897	74 655	80869	⊥ 5 142	148 413	219,6	1,6
Loures	172 998	13 596	43 559	20 600	35 867	31177	⊥ 1 942	26 257	92,3	2,1
Mafra	62 320	4 889	14 391	7 953	12 556	11779	⊥ 828	9 924	96,3	1,9
Moita	55 480	5 139	14 878	7 257	12 827	9906	⊥ 622	4 851	82,0	1,8
Montijo	42 716	4 124	9 825	5 005	8 654	8215	⊥ 542	6 351	99,2	2,1
Odivelas	122 637	8 274	30 273	14 102	25 506	23533	⊥ 1 525	19 424	89,3	2,2
Oeiras	145 561	7 196	23 443	11 384	26 408	30518	⊥ 1 922	44 690	156,5	2,0
Palmela	52	5 2	12 467	6 087	11 256	944	⊥ 583	7 0	98,1	1,9

	151	71				8		39		
Seixal	132 522	8 558	30 804	15 780	30 994	26 710	⊥ 1 624	18 052	89,7	2,0
Sesimbra	40 885	3 167	9 470	5 153	9 370	7 998	⊥ 574	5 153	90,0	1,6
Setúbal	101 628	8 977	22 976	11 561	22 508	19 196	⊥ 1 154	15 256	107,5	1,8
Sintra	311 202	18 351	64 044	39 362	76 335	66 819	⊥ 4 091	42 200	94,1	2,1
Vila Franca de Xira	113 372	7 469	25 084	13 649	26 041	24 215	⊥ 1 419	15 495	98,4	2,2
Alcácer do Sal	11 361	2 142	3 661	1 489	1 853	1 387	⊥ 64	765	81,5	1,3
Grândola	12 989	2 404	3 733	1 790	2 175	1 862	⊥ 82	943	85,9	1,2
Odemira	22 904	5 247	6 074	2 520	4 176	3 114	⊥ 163	1 610	81,7	1,2
Santiago do Cacém	26 088	3 881	6 630	2 790	5 106	4 602	⊥ 302	2 777	92,3	1,5
Sines	12 170	1 278	3 142	1 500	2 622	2 198	⊥ 173	1 257	128,7	1,6
Aljustrel	8 194	1 329	2 566	952	1 638	1 018	⊥ 37	654	87,9	1,4
Almodôvar	6 566	1 602	1 788	593	1 411	767	⊥ 20	385	79,5	1,2
Alvito	2	39	601	258	421	31	⊥ 14	170	66,7	1,4

	179	9				6				
Barrancos	1 588	241	437	242	288	281	⊥ 5	94	63,4	1,3
Beja	30 480	3 598	7 010	3 316	6 309	5036	⊥ 311	4 900	105,3	1,6
Castro Verde	6 320	926	1 904	729	1 200	869	⊥ 65	627	102,1	1,4
Cuba	4 241	647	1 254	487	805	633	⊥ 36	379	67,9	1,5
Ferreira do Alentejo	7 243	1 407	2 231	899	1 289	845	⊥ 50	522	73,0	1,5
Mértola	6 609	1 524	2 235	826	967	692	⊥ 28	337	66,6	0,7
Moura	12 765	2 449	3 690	1 714	2 352	1580	⊥ 71	909	77,5	1,3
Ourique	4 839	1 106	1 474	520	839	619	⊥ 16	265	77,3	1,1
Serpa	13 670	2 791	3 877	1 779	2 467	1648	⊥ 89	1 019	72,8	1,4
Vidigueira	5 114	877	1 518	628	918	714	⊥ 52	407	72,8	1,4
Almeirim	19 837	2 907	5 841	2 523	3 493	2809	⊥ 188	2 076	86,2	1,8
Alpiarça	6 558	1 004	2 168	687	1 178	850	⊥ 49	622	77,1	1,7

Azambuja	18 608	2 301	5 493	2 420	3 740	2914	171	1 569	106,2	1,9
Benavente	23 873	2 341	5 887	3 439	5 186	4237	276	2 507	94,4	2,1
Cartaxo	20 865	2 083	5 793	2 692	4 310	3433	236	2 318	86,5	1,7
Chamusca	8 943	1 565	3 138	1 197	1 513	927	46	557	71,7	1,5
Coruche	17 556	3 667	5 921	1 854	2 715	2058	127	1 214	76,8	1,4
Golegã	4 730	615	1 424	605	910	684	40	452	82,6	1,7
Rio Maior	17 993	2 253	5 309	2 412	3 474	2736	206	1 603	90,2	1,6
Salvaterra de Magos	18 900	3 248	5 348	2 542	3 522	2705	176	1 359	77,5	1,8
Santarém	53 309	5 821	14 305	5 809	10 165	8656	516	8 037	101,4	1,6
Alter do Chão	3 178	640	1 043	359	496	398	10	232	72,9	1,0
Arronches	2 833	644	891	321	441	331	12	193	72,0	1,1
Avis	4 052	847	1 305	493	646	473	29	259	74,1	1,1
Campo Maior	7 140	1 154	1 926	850	1 408	1125	64	613	94,0	1,6
Castelo de Vide	3 063	578	910	294	586	394	14	287	81,6	1,0
Crato	3 357	703	1 214	377	540	312	18	193	72,8	0,9
Elvas	19 507	2 652	5 155	2 472	3 978	3175	183	1 892	89,0	1,5
Fronteira	2 972	590	848	395	518	371	15	235	79,0	1,1
Gavião	3 774	814	1 448	438	607	303	19	145	71,8	0,9
Marvão	3 179	667	1 019	404	512	336	12	229	64,8	1,0
Monforte	2 840	678	899	310	424	327	23	179	73,9	1,3
Nisa	6 745	1	2 356	668	1 057	7	50	466	73,2	0,8

		419				29				
Ponte de Sor	14 609	2 696	4 520	1 873	2 386	1964	81	1 089	84,4	1,4
Portalegre	21 680	2 767	5 454	2 287	4 164	3304	148	3 556	104,1	1,5
Sousel	4 432	895	1 381	502	809	515	25	305	69,0	1,2
Alandroal	5 178	1 050	1 841	702	788	518	21	258	64,5	1,1
Arraiolos	6 451	1 106	1 862	812	1 222	916	46	487	73,3	1,4
Borba	6 483	1 243	1 899	848	1 057	929	49	458	73,9	1,6
Estremoz	12 652	2 244	3 551	1 341	2 279	1978	97	1 162	93,9	1,3
Évora	48 448	4 684	10 870	5 281	9 072	9078	508	8 955	117,3	1,7
Montemor-o-Novo	15 342	2 901	4 723	1 700	2 476	2081	116	1 345	86,8	1,5
Mora	4 474	960	1 579	454	729	453	19	280	82,4	1,0
Mourão	2 251	434	705	320	400	280	12	100	69,9	1,3
Portel	5 627	1 080	1 926	770	872	668	45	266	64,8	1,4
Redondo	6 130	1 078	1 938	877	1 045	751	42	399	71,9	1,4
Reguengos de Monsaraz	9 286	1 622	2 726	1 185	1 508	1345	76	824	89,4	1,5
Vendas Novas	10 175	1 489	3 036	1 207	1 934	1511	91	907	95,2	1,7

Viana do Alentejo	4 920	933	1 360	671	894	689	34	339	79,3	1,4
Vila Viçosa	7 258	1 082	2 119	996	1 234	1156	60	611	83,4	1,6
Albufeira	34 328	3 083	7 184	4 315	7 958	7354	488	3 946	112,0	1,0
Alcoutim	2 687	760	958	305	295	237	11	121	67,5	0,6
Aljezur	5 216	980	1 274	510	950	969	50	483	63,1	0,9
Castro Marim	5 909	971	1 778	804	1 061	807	37	451	71,7	0,7
Faro	55 160	4 508	11 908	5 258	11 008	10922	622	10 934	132,5	1,6
Lagoa	19 377	1 864	4 813	2 452	4 559	3547	197	1 945	89,8	1,1
Lagos	26 179	2 769	5 709	3 009	5 768	5378	328	3 218	93,8	1,1
Loulé	60 330	6 866	15 520	6 823	12 642	11076	714	6 689	105,9	1,0
Monchique	5 446	1 088	1 825	517	829	778	43	366	61,9	1,1
Olhão	37 894	3 878	10 137	4 880	8 232	6417	410	3 940	81,1	1,7
Portimão	46 899	4 668	10 594	5 385	10 600	8648	620	6 384	103,5	1,2
São Brás de Alportel	9 127	906	2 611	1 010	1 672	1687	108	1 133	84,8	1,5
Silves	31 997	4 207	8 524	3 947	6 896	5327	321	2 775	76,9	1,1
Tavira	22 654	3 195	6 209	2 589	4 093	3815	235	2 518	92,0	0,9
Vila do Bispo	4 647	632	1 329	593	916	761	45	371	64,6	0,8
Vila Real de Santo António	16 182	1 591	4 574	2 187	3 505	2712	168	1 445	91,8	0,9

Vila do Porto	4 589	476	1 332	787	892	675	56	371	89,7	1,5
Lagoa [R.A.A.]	11 413	1 208	3 527	2 422	2 180	1128	86	862	74,2	2,8
Nordeste	4 061	424	1 373	844	777	419	13	211	62,5	1,8
Ponta Delgada	56 380	5 343	12 375	10 332	11 801	7944	662	7 923	107,8	2,3
Povoação	5 209	732	1 689	1 105	879	485	26	293	66,3	1,6
Ribeira Grande	24 623	3 192	7 146	5 556	4 366	2467	192	1 704	71,1	2,8
Vila Franca do Campo	9 045	1 352	2 931	1 890	1 477	799	50	546	65,0	2,6
Angra do Heroísmo	29 609	2 810	8 851	4 842	5 547	3758	264	3 537	94,7	2,2
Vila da Praia da Vitória	17 661	1 879	5 910	2 847	3 346	2265	118	1 296	74,7	2,2
Santa Cruz da Graciosa	3 741	529	1 357	583	631	353	20	268	73,1	1,5
Calheta [R.A.A.]	3 216	536	1 177	478	570	253	13	189	77,1	1,3
Velas	4 620	497	1 659	658	915	520	38	333	83,1	1,6

Lajes do Pico	4 088	409	1 541	628	682	484	⊥ 27	317	70,0	1,4
Madalena	5 170	435	1 941	651	949	738	⊥ 62	394	89,1	1,7
São Roque do Pico	2 941	221	1 077	422	529	408	⊥ 27	257	81,5	1,4
Horta	12 591	914	3 704	2 009	2 531	1868	⊥ 137	1 428	90,7	2,0
Lajes das Flores	1 283	141	479	186	227	143	⊥ 11	96	74,8	1,4
Santa Cruz das Flores	1 966	158	690	277	433	221	⊥ 8	179	88,4	1,9
Corvo	369	42	135	64	57	46	⊥ 1	24	76,2	2,4
Calheta [R.A.M.]	9 806	1 926	3 369	1 265	1 363	1067	⊥ 79	737	62,8	1,4
Câmara de Lobos	28 221	4 927	9 039	4 973	4 838	2813	⊥ 234	1 397	58,3	2,5
Funchal	95 487	8 827	24 428	13 207	17 527	15081	⊥ 1 241	15 176	114,3	2,0
Machico	18 370	2 508	6 335	2 820	3 021	2055	⊥ 190	1 441	78,2	2,0
Ponta do Sol	7 246	1 249	2 363	1 123	1 098	791	⊥ 54	568	55,2	1,8
Porto Moniz	2 380	610	842	331	263	197	⊥ 11	126	56,9	1,2
Ribeira Brava	11 005	2 191	3 429	1 626	1 595	1249	⊥ 79	836	68,4	1,8
Santa Cruz	34 964	2 837	7 860	5 431	7 273	6284	⊥ 679	4 600	71,5	2,2
Santana	6 708	1 512	2 307	863	853	676	⊥ 69	428	58,3	1,4
São Vicente	4 921	1 140	1 646	696	589	508	⊥ 33	309	61,0	1,3
Porto Santo	4 665	399	1 240	698	975	852	⊥ 58	443	93,5	1,1

13. SEGMENTATION MODEL RESULTS AFTER ADDING NEW SOCIO-ECONOMIC FEATURES

Cluster 0

Rel Freq. of Donors per ***Region***

Vale do Tejo	0,33
Entre-Douro-e-Minho	0,28
Lisboa	0,14
Beira Litoral	0,11
Algarve	0,03
Alentejo	0,02
NOT FOUND	0,02
Beira Interior	0,02
Trás-os-Montes e Alto Douro	0,02
Açores	0,01
Madeira	0,01

Rel Freq. of Donors per ***Gender***

Feminino	0,71
Masculino	0,29
other	0

Rel Freq. of Donors Registered as AMI_friend

1	0,59
0	0,41

Rel Freq. of Donors ***per Registration Source Group***

AMI RESOURCES/DEPARTMENTS	0,57
AUCHAN CAMPAIGN	0,14
SPONTANEOUS REGISTRATION	0,1
CHRISTMAS CAMPAIGNS	0,06
TMN CAMPAIGNS	0,05
DONORS	0,03
EMERGENCY CAMPAIGNS	0,03
NATIONAL CAMPAIGNS	0,01
OTHERS	0,01
INTERNATIONAL CAMPAIGNS	0
CORPORATE PARTNERSHIPS	0
TRAINING	0
ENVIRONMENT	0

Rel Freq. of Donors ***per Company Field Description***

individuals	1

Rel Freq. of Donors ***per Company Legal Form***

individuals	1

Avg Total Value Donate Per Donor	*Avg Total Number of Contributions Per Donor*	*Avg Number of Days Since Donor Last Contribution (Recency)*	*Median Number of Days Between Contribution (Frequency)*	*Avg Purchasing Power*	*Avg Number of People per Household*	*Avg Education Score*
818,16	16,01	2506,6	127	120,22	1,81	2,86

Cluster 1

	Rel Freq. of Donors ***per Region***
Vale do Tejo	0,28
Lisboa	0,25
Entre-Douro-e-Minho	0,23
Beira Litoral	0,07
NOT FOUND	0,05
Alentejo	0,04
Algarve	0,03
Beira Interior	0,02
Açores	0,01
Madeira	0,01
Trás-os-Montes e Alto Douro	0,01

	Rel Freq. of Donors ***per Gender***
Masculino	0,63
Feminino	0,37
other	0

	Rel Freq. of Donors Registered as AMI_friend
0	1
1	0

	Rel Freq. of Donors per Registration Source Group
OTHERS	0,91
SPONTANEOUS REGISTRATION	0,06
NATIONAL CAMPAIGNS	0,01
INTERNATIONAL CAMPAIGNS	0
ENVIRONMENT	0
TMN CAMPAIGNS	0
AMI RESOURCES/DEPARTMENTS	0
CORPORATE PARTNERSHIPS	0
AUCHAN CAMPAIGN	0
EMERGENCY CAMPAIGNS	0
TRAINING	0
DONORS	0
CHRISTMAS CAMPAIGNS	0

	Rel Freq. of Donors ***per Company Field Description***
individuals	1

Avg Total Value Donate Per Donor	*Avg Total Number of Contributions Per Donor*	*Avg Number of Days Since Donor Last Contribution (Recency)*	*Median Number of Days Between Contribution (Frequency)*	*Avg Purchasing Power*	*Avg Number of People per Household*	*Avg Education Score*
0,35	0,01	13,21	-0,9	136,8	1,76	2,96

Cluster 2

Rel Freq. of Donors ***per Region***

Vale do Tejo	0,25
Entre-Douro-e-Minho	0,21
Lisboa	0,19
Beira Litoral	0,12
NOT FOUND	0,07
Alentejo	0,04
Algarve	0,03
Beira Interior	0,03
Madeira	0,02
Açores	0,02
Trás-os-Montes e Alto Douro	0,02

Rel Freq. of Donors ***per Gender***

company	1

Rel Freq. of Donors Registered as AMI_friend

0	0,97
1	0,03

Rel Freq. of Donors ***per Registration Source Group***

OTHERS	0,5
SPONTANEOUS REGISTRATION	0,21
TMN CAMPAIGNS	0,05
ENVIRONMENT	0,05
AMI RESOURCES/DEPARTMENTS	0,05
CORPORATE PARTNERSHIPS	0,04
EMERGENCY CAMPAIGNS	0,03
INTERNATIONAL CAMPAIGNS	0,02
CHRISTMAS CAMPAIGNS	0,01
DONORS	0,01
NATIONAL CAMPAIGNS	0,01
TRAINING	0,01
AUCHAN CAMPAIGN	0

Rel Freq. of Donors ***per Company Field Description***

not found	0,33
COMÉRCIO E VEÍCULOS	0,19
INDÚSTRIAS TRANSFORMADORAS	0,09

ACTIVIDADES DE CONSULTORIA, CIENTÍFICAS, TÉCNICAS E SIMILARES	0,08
ALOJAMENTO, RESTAURAÇÃO E SIMILARES	0,06
ACTIVIDADES DE INFORMAÇÃO E DE COMUNICAÇÃO	0,04
ACTIVIDADES DE SAÚDE HUMANA E APOIO SOCIAL	0,04
CONSTRUÇÃO	0,03
ACTIVIDADES ADMINISTRATIVAS E DOS SERVIÇOS DE APOIO	0,03
ACTIVIDADES IMOBILIÁRIAS	0,02
EDUCAÇÃO	0,02
TRANSPORTES E ARMAZENAGEM	0,02
ACTIVIDADES FINANCEIRAS E DE SEGUROS	0,01
OUTRAS ACTIVIDADES DE SERVIÇOS	0,01
ACTIVIDADES ARTÍSTICAS, DE ESPECTÁCULOS, DESPORTIVAS E RECREATIVAS	0,01
CAPTAÇÃO, TRATAMENTO E DISTRIBUIÇÃO DE ÁGUA; SANEAMENTO,GESTÃO DE RESÍDUOS E DESPOLUIÇÃO	0,01
AGRICULTURA, PRODUÇÃO ANIMAL, CAÇA, FLORESTA E PESCA	0,01
ADMINISTRAÇÃO PÚBLICA E DEFESA; SEGURANÇA SOCIAL OBRIGATÓRIA	0
INDÚSTRIAS EXTRACTIVAS	0
ELECTRICIDADE, GÁS, VAPOR, ÁGUA QUENTE E FRIA E AR FRIO	0

Avg Total Value Donate Per Donor	*Avg Total Number of Contributions Per Donor*	*Avg Number of Days Since Donor Last Contribution (Recency)*	*Median Number of Days Between Contribution (Frequency)*	*Avg Purchasing Power*	*Avg Number of People per Household*	*Avg Education Score*
1358,32	2,31	1764,72	-1	128,8	1,77	2,91

Cluster 3

*Rel Freq. of Donors **per Region***

Vale do Tejo	0,31
Entre-Douro-e-Minho	0,21
Lisboa	0,15
Beira Litoral	0,12
NOT FOUND	0,05
Alentejo	0,05
Algarve	0,04
Beira Interior	0,03
Madeira	0,03
Trás-os-Montes e Alto Douro	0,02
Açores	0,01

*Rel Freq. of Donors **per Gender***

Feminino	0,57
Masculino	0,43
other	0

Rel Freq. of Donors Registered as AMI_friend