**PROCESS OVERVEIW**

***Problem Statement:***

The current business state of a Portuguese banking institution, Banco de Portugal, is one of fiscal instability, lost revenue and lowered long-term client engagement, in comparison to the last fiscal year (Moro, Cortez, & Rita, 2014). To maintain corporate competitiveness, Banco de Portugal initiated a telemarketing campaign based on the concept that their clientele weren’t depositing as frequently as they had been in the past (Moro, Cortez, & Rita, 2014). The marketing campaign was deployed via direct phone calls to promote the subscription of long-term deposits. With the desire to optimize output and reduce human and financial resources for the campaign, a study was established to determine which targeted clients would most likely respond positively to the telemarketing scheme and subscribe to the long-term deposits.

Distinguishing the success rate of the telemarketing phone calls is of high value as it highlights whether the retail bank in question is able to successfully reach consumers and sell them the campaign. More specifically, which clients are most financially viable to target (in terms of reduced opportunity cost and avoiding financing marketing ploys aimed at the wrong clientele). Marketing campaigns are a typical strategy implemented to enhance business engagement. By using this targeted marketing ploy, the retail banking firm is aiming to meet a desired business state of increased client long-term deposits and consequential financial stability.

This problem has been addressed by past research projects, across various contexts (Kim, Lee, Jo, & Cho, 2015), (Landreth O. , 1992) , (Tang, 2014). The eventuated success rate of marketing models are a fundamental component to positively received campaigns. Due to the competitive nature of corporate marketing, data-focused insight and analytical studies are highly prevalent. With specific reference to the data itself, it was retrieved from the original study stemmed from the campaign from 2008-2011 (Moro, Cortez, & Rita, 2014).

***Industry/ Domain:***

The banking industry is that in question, with strong focus on marketing operations. With this in mind, the retail banking sector is facing a significant amount of disruption as the digital age is exponentially changes business processes and client behaviour. Specifically the shift towards mobile/ online banking, away from having to go to a physical bank to reap benefits of trade (Lee & Lee, 2020). High competition is prevalent from disruptive start-ups and “neobanks” (Hopkinson & Klarova, 2019) that are changing service expectations - which is only further highlighting that efficiency gains from technology are of elevated value to the consumers.

These factors all motivate the need to adaptively strategize and implement new business processes and market various revenue-stimulating sectors, as is seen in this particular study (Moro, Cortez, & Rita, 2014).

Although the value chain in question centres around fiscal activities (wealth management, financial guidance and asset/liability administration ect.), the study is specifically focused on the success rate of a marketing campaign. Due to the generalizability of such marketing schemes, this project is henceforth highly relevant to multiple industries facing the need to instigate competitive marketing operations.

***Stakeholders:***

The stakeholders in questions are in direct relation to the Banco de Portugal. This covers the official Board of Directors, Board of Auditors, Advisory Board and shareholders of the institution. Each stakeholder is impacted by the success rate of the marketing campaign, promoting long-term deposits. The higher the success rate, the higher the financial investment actions of the banking entity (on product/services with a higher RoR (rate of return). Increasing the banks investment capabilities, increases the services available to clients. For obvious reasons, shareholders will only benefit from increased revenue and stability of long-term deposits, an so forth. From a client perspective, long-term benefits include increased saving capabilities, decreased investment volatility, and increased interest rates.

In line with the project, it can be assumed that clientele wish to gain these competitive rates on their long-term deposits and shareholders will expect to benefit from increased financial flow and business activities to promote the economic success of their institutional foundations.

***Business Question:***

The main business question that requires attention is: *Which existing customers would have a higher probability of responding positively to a long-term deposit marketing campaign?*

The aim is to deliver valuable customer insight to the stakeholders that will increase the chance of campaign success.

The required rate of accuracy should be very high as the consequences of incorrect predictability would result in the investment of unsuccessful marketing campaign, increased opportunity cost (missing out on better opportunities/client engagement), reduced revenue and investment capabilities, lowered financial certainty/ increased volatility.

***Data Question:***

From a data science perspective, the question we are attempting to answer is: *Can a Machine Learning model predict which clients are most-likely to successfully respond to telemarketing calls aimed at selling long-term deposits?*

The data required to answer this question involves:

* Survey data of the marketing campaign
* Attributes of the targeted clients from pre-existing data from Banco de Portugal
* Resulting response/ action of the customer (successful, unsuccessful)

***Data:***

The data was sourced from the UCI Machine Learning Repository (UCI, 2014), based on the aforementioned 2014 study (Moro, Cortez, & Rita, 2014). The data is related with direct marketing campaigns of the Portuguese banking institution, of which were stemmed from direct phone calls. Often, more than one contact to the same client was required, in order to access if the product in question (long-term deposit) would be subscribed ('yes') or not ('no'). There were originally four datasets in question, as follows:

1. bank-additional-full.csv with all examples (41,188) and 20 inputs, ordered by date (from May 2008 to November 2010), very close to the data analyzed in [Moro et al., 2014]
2. bank-additional.csv with 10% of the examples (4119), randomly selected from 1), and 20 inputs.
3. bank-full.csv with all examples (45,211) and 17 inputs, ordered by date (older version of this dataset with less inputs).
4. bank.csv with 10% of the examples (4521) and 17 inputs, randomly selected from 3 (older version of this dataset with less inputs).   
   The smallest datasets are provided to test more computationally demanding machine learning algorithms (e.g. SVM).

In regards to the reliability of the data, it was established within a highly cited and publicised research paper (Moro, Cortez, & Rita, 2014). The original collection was released publicly for future research and educational purposes, as well as an adaption by the Banco de Portugal that contained revised attributes to accommodate for socio economic factors. Coinciding with the fact that that the collection and study of the data acquired spanned from 2008 to 2014, I can contest that the source is very reliable. With respect to the raw data, the completeness and quality of the figures is varied. There are significant incidents that have unknown variables, as would be expected in the case of telemarketing data. In hindsight, a lot of wrangling will have to be done to get the dataset to a stage that a predictive model can be successfully built upon.

The original data was generated for the founding journal (Moro, Cortez, & Rita, 2014) in the following stages:

1. A Portuguese retail bank was addressed, with data collected from 2008 to 2013 (note the inclusion of the financial crisis).
2. A significant set of 150 features was analysed related with bank client, product and social-economic attributes.
3. A semi-automatic feature selection was initiated in the modelling phase within the study, resulting in a reduced set of 21 attributes.

Although this targeted data was publicised for future studies, the exact figures are not available on an ongoing bases. In the context of the specialized curation of the data with reference to the retail banking case study, this may present as a limitation as future comparisons will not be easily made. However, due to the relatability of the data in correspondence to a multitude of industries, the potential for replication to some degree is implied.

**DATA SCIENCE PROCESS**

***Data Analysis:***

Chart, line chart, histogram

Description automatically generatedThree insights:

1. Chart, scatter chart

   Description automatically generatedAfter categorising client ages into bins, the group with the highest number (count) of customers that responded positively to the telemarketing campaign were in their “30s”. HOWEVER once these figures were normalized, the finding actually showed that “20s” were more likely to subscribe, as well as those in their “60s” and “70s+”. This was also efficiently shown in the KDE plot, distinguishing the response across the age groups in smooth manner.
2. Response result on duration and number of calls: Higher subscription rate when the client received less than 5 telemarketing calls. In other words, client were most likely to reject the campaign if they received more than 5 calls. The plot significantly distinguishes the clients which subscribed to the long term deposit from the clients who did not. Clients who subscribed to the deposit where contacted fewer times and had longer call duration
3. Chart, bar chart

   Description automatically generatedResponse against client occupation, as a normalized proportion: clients that worked in admin had the highest percentage of subscription rates. Retired client were also more likely to subscribe. Blues collar workers, on the other hand, saw a noticeably bigger segment that did not subscribe. Although not as extreme, this same observation can be made for those working in the service industry.

***Modelling:***

Feature Engineering:

* Dummy variables (to transform categorical (nominal) variables to numerical
* Normalized scaler (to standardize dummy with original numerical data)
* SMOTE: (synthetic resampling to correct imbalanced classification) Chawla, N. V., et al. “SMOTE: Synthetic Minority Over-Sampling Technique.” *Journal of Artificial Intelligence Research*,

Supervised Learning: Classification model

1. Base: Logistic regression (with and without synthetic sampling SMOTE to overcome imbalanced classifiers)

* Cramer, J. S. (2002). [*The origins of logistic regression*](https://papers.tinbergen.nl/02119.pdf) (PDF) (Technical report). **119**. Tinbergen Institute. pp. 167–178. [doi](https://en.wikipedia.org/wiki/Doi_(identifier)):[10.2139/ssrn.360300](https://doi.org/10.2139%2Fssrn.360300).

1. Complex: Support Vector Machine

* *[Cortes, Corinna](https://en.wikipedia.org/wiki/Corinna_Cortes); Vapnik, Vladimir N. (1995).*[*"Support-vector networks"*](http://image.diku.dk/imagecanon/material/cortes_vapnik95.pdf)*(PDF).*[*Machine Learning*](https://en.wikipedia.org/wiki/Machine_Learning_(journal))*.****20****(3): 273–297. [CiteSeerX](https://en.wikipedia.org/wiki/CiteSeerX_(identifier))*[*10.1.1.15.9362*](https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.15.9362)

Unsupervised Learning: Clustering

* K-means: An iterative algorithm that attempts to partition the data into distinct subgroups
* Based on client “personas”
* Will be able to provide valuable insight as to which clients personas are most likely to respond positively to the telemarketing campaign

Chart, bar chart

Description automatically generated***Outcomes:***

* + Logreg:
    - Accuracy: train 91.19%, test 90.86%
    - Recall: didn’t subscribe (0) 97%, subscribed (1) 41%
    - Precision: didn’t subscribe (0) 93%, subscribed (1) 66%
    - ROC curve area: train 94%, test 93%
  + Logreg with SMOTE:
    - Accuracy: train 88.97%, test 86.75%
    - Chart, bar chart

      Description automatically generatedRecall: didn’t subscribe (0) 87%, subscribed (1) 87%
    - Precision: didn’t subscribe (0) 98%, subscribed (1) 46%
    - ROC curve area: train 94%, test 94%
  + SVM:
    - Accuracy: train 90.51%, test 90.47%
    - Recall: didn’t subscribe (0) 98%, subscribed (1) 32%
    - Precision: didn’t subscribe (0) 92%, subscribed (1) 68%
  + Kmeans: (Unsupervised, k=2)
    - Cluster 1:
      * Response: Less likely to subscribe
      * Age: 40+
      * Education: Primary/ basic education
      * Marital: Married
      * Job: Blue-Collar
    - Cluster 2:
      * Response: more likely to subscribe
      * Age: Less than 40
      * Education: Tertiary/ professional
      * Marital: Married, but also highest account for singles
      * Job: administration/ tech/ services

***Implementation:***

Supervised ML:

* Recall and Precision were the main identifiers of variance across the models
* Whilst the evaluation metrics saw little divergence across the model for non-subscribing clients, there were significant differences across the models for subscribing customers.
* Taking in consideration that accuracy can be a misleading metric for imbalanced classifiers we will focus on the other metrics
* Extremely low recall for the unsampled logreg and SVM models suggest that the sensitivity of the model is rather low with references to detecting positive responses
* Although the precision score is low for the resampled logreg (relatively speaking) for the subscribing clients, it was the highest in the non-subscribing clients.
* From these figures I can say I have been able to most aptly construct a model to predict the responses of clients by using a Logistic Regression model on a synthetically resampled dataset.

Unsupervised ML:

* It is essential for banks to enrich marketing strategies and improve effectiveness. Understanding customer clustering leads to more effective campaigns, informed product design and greater overall client satisfaction.
* The main goal is to increase the effectiveness and efficiency of the banks telemarketing campaign, and this has been successfully achieved through todays findings. By initiating managerial decisions based of informed, data-driven models such as this, operational effectiveness is optimised.

**Results:**

* ***Data Answer:***
* ***Business Answer:***
* ***Response to Stakeholders:***
* ***End-to-End Solution:***

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