



# A data-driven approach to predict the success of bank telemarketing



Sérgio Moro <sup>a,\*</sup>, Paulo Cortez <sup>b</sup>, Paulo Rita <sup>a</sup>

<sup>a</sup> ISCTE-IUL, Business Research Unit (BRU-IUL), Lisboa, Portugal

<sup>b</sup> ALGORITMI Research Centre, Univ. of Minho, 4800-058 Guimarães, Portugal

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## ABSTRACT

We propose a data mining (DM) approach to predict the success of telemarketing calls for selling bank long-term deposits. A Portuguese retail bank was addressed, with data collected from 2008 to 2013, thus including the effects of the recent financial crisis. We analyzed a large set of 150 features related with bank client, product and social-economic attributes. A semi-automatic feature selection was explored in the modeling phase, performed with the data prior to July 2012 and that allowed to select a reduced set of 22 features. We also compared four DM models: logistic regression, decision trees (DTs), neural network (NN) and support vector machine. Using two metrics, area of the receiver operating characteristic curve (AUC) and area of the LIFT cumulative curve (ALIFT), the four models were tested on an evaluation set, using the most recent data (after July 2012) and a rolling window scheme. The NN presented the best results (AUC = 0.8 and ALIFT = 0.7), allowing to reach 79% of the subscribers by selecting the half better classified clients. Also, two knowledge extraction methods, a sensitivity analysis and a DT, were applied to the NN model and revealed several key attributes (e.g., Euribor rate, direction of the call and bank agent experience). Such knowledge extraction confirmed the obtained model as credible and valuable for telemarketing campaign managers.

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## 1. Introduction

Marketing selling campaigns constitute a typical strategy to enhance business. Companies use direct marketing when targeting segments of customers by contacting them to meet a specific goal. Centralizing customer remote interactions in a contact center eases operational management of campaigns. Such centers allow communicating with customers through various channels, telephone (fixed-line or mobile) being one of the most widely used. Marketing operationalized through a contact center is called telemarketing due to the remoteness characteristic [16]. Contacts can be divided into inbound and outbound, depending on which side triggered the contact (client or contact center), with each case posing different challenges (e.g., outbound calls are often considered more intrusive). Technology enables rethinking marketing by focusing on maximizing customer lifetime value through the evaluation of available information and customer metrics, thus allowing us to build longer and tighter relations in alignment with business demand [28]. Also, it should be stressed that the task of selecting the best set of clients, i.e., that are more likely to subscribe a product, is considered NP-hard in Ref. [31].

Decision support systems (DSSs) use information technology to support managerial decision making. There are several DSSs sub-fields, such as personal and intelligent DSSs. Personal DSSs are related with small-scale systems that support a decision task of one manager,

while intelligent DSSs use artificial intelligence techniques to support decisions [1]. Another related DSS concept is Business Intelligence (BI), which is an umbrella term that includes information technologies, such as data warehouses and data mining (DM), to support decision making using business data [32]. DM can play a key role in personal and intelligent DSSs, allowing the semi-automatic extraction of explanatory and predictive knowledge from raw data [34]. In particular, classification is the most common DM task [10] and the goal is to build a data-driven model that learns an unknown underlying function that maps several input variables, which characterize an item (e.g., bank client), with one labeled output target (e.g., type of bank deposit sell: “failure” or “success”).

There are several classification models, such as the classical Logistic Regression (LR), decision trees (DTs) and the more recent neural networks (NNs) and support vector machines (SVMs) [13]. LR and DT have the advantage of fitting models that tend to be easily understood by humans, while also providing good predictions in classification tasks. NN and SVM are more flexible (i.e., no a priori restriction is imposed) when compared with classical statistical modeling (e.g., LR) or even DT, presenting learning capabilities that range from linear to complex nonlinear mappings. Due to such flexibility, NN and SVM tend to provide accurate predictions, but the obtained models are difficult to be understood by humans. However, these “black box” models can be opened by using a sensitivity analysis, which allows us to measure the importance and effect of particular input in the model output response [7]. When comparing DT, NN and SVM, several studies have shown different classification performances. For instance, SVM provided better

\* Corresponding author.

E-mail address: [scmoro@gmail.com](mailto:scmoro@gmail.com) (S. Moro).

results in Refs. [6,8], comparable NN and SVM performances were obtained in Ref. [5], while DT outperformed NN and SVM in Ref. [24]. These differences in performance emphasize the impact of the problem context and provide a strong reason to test several techniques when addressing a problem before choosing one of them [9].

DSS and BI have been applied to banking in numerous domains, such as credit pricing [25].

However, the research is rather scarce in terms of the specific area of banking client targeting. For instance, Ref. [17] described the potential usefulness of DM techniques in marketing within Hong-Kong banking sector but no actual data-driven model was tested. The research of Ref. [19] identified clients for targeting at a major bank using pseudo-social networks based on relations (money transfers between stakeholders). Their approach offers an interesting alternative to traditional usage of business characteristics for modeling.

In previous work [23], we have explored data-driven models for modeling bank telemarketing success. Yet, we only achieved good models when using attributes that are only known on call execution, such as call duration. Thus, while providing interesting information for campaign managers, such models cannot be used for prediction. In what is more closely related with our approach, Ref. [15] analyzed how a mass media (e.g., radio and television) marketing campaign could affect the buying of a new bank product. The data was collected from an Iran bank, with a total of 22,427 customers related with a six month period, from January to July of 2006, when the mass media campaign was conducted. It was assumed that all customers who bought the product (7%) were influenced by the marketing campaign. Historical data allowed the extraction of a total of 85 input attributes related with recency, frequency and monetary features and the age of the client. A binary classification task was modeled using a SVM algorithm that was fed with 26 attributes (after a feature selection step), using 2/3 randomly selected customers for training and 1/3 for testing. The classification accuracy achieved was 81% and through a Lift analysis [3], such model could select 79% of the positive responders with just 40% of the customers. While these results are interesting, a robust validation was not conducted. Only one holdout run (train/test split) was considered. Also, such random split does not reflect the temporal dimension that a real prediction system would have to follow, i.e., using past patterns to fit the model in order to issue predictions for future client contacts.

In this paper, we propose a personal and intelligent DSS that can automatically predict the result of a phone call to sell long term deposits by using a DM approach. Such DSS is valuable to assist managers in prioritizing and selecting the next customers to be contacted during bank marketing campaigns. For instance, by using a Lift analysis that analyzes the probability of success and leaves to managers only the decision on how many customers to contact. As a consequence, the time and costs of such campaigns would be reduced. Also, by performing fewer and more effective phone calls, client stress and intrusiveness would be diminished. The main contributions of this work are:

- We focus on feature engineering, which is a key aspect in DM [10], and propose generic social and economic indicators in addition to the more commonly used bank client and product attributes, in a total of 150 analyzed features. In the modeling phase, a semi-automated process (based on business knowledge and a forward method) allowed to reduce the original set to 22 relevant features that are used by the DM models.
- We analyze a recent and large dataset (52,944 records) from a Portuguese bank. The data were collected from 2008 to 2013, thus including the effects of the global financial crisis that peaked in 2008.
- We compare four DM models (LR, DT, NN and SVM) using a realistic rolling window evaluation and two classification metrics. We also show how the best model (NN) could benefit the bank telemarketing business.

The paper is organized as follows: Section 2 presents the bank data and DM approach; Section 3 describes the experiments conducted and

analyzes the obtained results; finally, conclusions are drawn in Section 4.

## 2. Materials and methods

### 2.1. Bank telemarketing data

This research focus on targeting through telemarketing phone calls to sell long-term deposits. Within a campaign, the human agents execute phone calls to a list of clients to sell the deposit (outbound) or, if meanwhile the client calls the contact-center for any other reason, he is asked to subscribe the deposit (inbound). Thus, the result is a binary unsuccessful or successful contact.

This study considers real data collected from a Portuguese retail bank, from May 2008 to June 2013, in a total of 52,944 phone contacts. The dataset is unbalanced, as only 6557 (12.38%) records are related with successes. For evaluation purposes, a time ordered split was initially performed, where the records were divided into training (four years) and test data (one year). The training data is used for feature and model selection and includes all contacts executed up to June 2012, in a total of 51,651 examples. The test data is used for measuring the prediction capabilities of the selected data-driven model, including the most recent 1293 contacts, from July 2012 to June 2013.

Each record included the output target, the contact outcome (“failure”, “success”), and candidate input features. These include telemarketing attributes (e.g., call direction), product details (e.g., interest rate offered) and client information (e.g., age). These records were enriched with social and economic influence features (e.g., unemployment variation rate), by gathering external data from the central bank of the Portuguese Republic statistical web site<sup>1</sup>. The merging of the two data sources led to a large set of potentially useful features, with a total of 150 attributes, which are scrutinized in Section 2.4.

### 2.2. Data mining models

In this work, we test four binary classification DM models, as implemented in the rminer package of the R tool [5]: logistic regression (LR), decision trees (DTs), neural network (NN) and support vector machine (SVM).

The LR is a popular choice (e.g., in credit scoring) that operates a smooth nonlinear logistic transformation over a multiple regression model and allows the estimation of class probabilities [33]:  $p(c|x_k) =$

$$\frac{1}{1 + \exp\left(-\left(w_0 + \sum_{i=1}^M w_i x_{k,i}\right)\right)}, \text{ where } p(c|x) \text{ denotes the probability of class } c \text{ given}$$

the  $k$ -th input example  $x_k = (x_{k,1}, \dots, x_{k,M})$  with  $M$  features and  $w_i$  denotes a weight factor, adjusted by the learning algorithm. Due to the additive linear combination of its independent variables ( $x$ ), the model is easy to interpret. Yet, the model is quite rigid and cannot model adequately complex nonlinear relationships.

The DT is a branching structure that represents a set of rules, distinguishing values in a hierarchical form [2]. This representation can be translated into a set of IF-THEN rules, which are easy to understand by humans.

The multilayer perceptron is the most popular NN architecture [14]. We adopt a multilayer perceptron with one hidden layer of  $H$  hidden nodes and one output node. The  $H$  hyperparameter sets the model learning complexity. A NN with a value of  $H = 0$  is equivalent to the LR model, while a high  $H$  value allows the NN to learn complex nonlinear relationships. For a given input  $x_k$  the state of the  $i$ -th neuron ( $s_i$ ) is computed by:  $s_i = f(w_{i,0} + \sum_{j \in P_i} w_{i,j} \times s_j)$ , where  $P_i$  represents the set of nodes reaching node  $i$ ;  $f$  is the logistic function;  $w_{i,j}$  denotes the weight of the connection between nodes  $j$  and  $i$ ; and  $s_1 = x_{k,1}, \dots, s_M = x_{k,M}$ . Given that the logistic function is used, the

<sup>1</sup> <http://www.bportugal.pt/EstatisticasWeb/Default.aspx?Lang=en-GB>

output node automatically produces a probability estimate ( $\epsilon[0,1]$ ). The NN final solution is dependent of the choice of starting weights. As suggested in Ref. [13], to solve this issue, the **rminer** package uses an ensemble of  $N_r$  different trained networks and outputs the average of the individual predictions [13].

The SVM classifier [4] transforms the input  $x \in \mathcal{X}^M$  space into a high  $m$ -dimensional feature space by using a nonlinear mapping that depends on a kernel. Then, the SVM finds the best linear separating hyperplane, related to a set of support vector points, in the feature space. The **rminer** package adopts the popular Gaussian kernel [13], which presents less parameters than other kernels (e.g., polynomial):  $K(x, x') = \exp(-\gamma \|x - x'\|^2)$ ,  $\gamma > 0$ . The probabilistic SVM output is given by Ref. [35]:  $f(x_i) = \sum_{j=1}^m y_j \alpha_j K(x_j, x_i) + b$  and  $p(i) = 1/(1 + \exp(Af(x_i) + B))$ , where  $m$  is the number of support vectors,  $y_i \in \{-1, 1\}$  is the output for a binary classification,  $b$  and  $\alpha_j$  are the coefficients of the model, and  $A$  and  $B$  are determined by solving a regularized maximum likelihood problem.

Before fitting the NN and SVM models, the input data is first standardized to a zero mean and one standard deviation [13]. For DT, **rminer** adopts the default parameters of the **rpart** R package, which implements the popular CART algorithm [2]. For the LR and NN learning, **rminer** uses the efficient BFGS algorithm [22], from the family of quasi-Newton methods, while SVM is trained using the sequential minimal optimization (SMO) [26]. The learning capabilities of NN and SVM are affected by the choice of their hyperparameters ( $H$  for NN;  $\gamma$  and  $C$ , a complex penalty parameter, for SVM). For setting these values, **rminer** uses grid search and heuristics [5].

Complex DM models, such as NN and SVM, often achieve accurate predictive performances. Yet, the increased complexity of NN and SVM makes the final data-driven model difficult to be understood by humans. To open these black-box models, there are two interesting possibilities, rule extraction and sensitivity analysis. Rule extraction often involves the use of a white-box method (e.g., decision tree) to learn the black-box responses [29]. The sensitivity analysis procedure works by analyzing the responses of a model when a given input is varied through its domain [7]. By analyzing the sensitivity responses, it is possible to measure input relevance and average impact of a particular input in the model. The former can be shown visually using an input importance bar plot and the latter by plotting the Variable Effect Characteristic (VEC) curve. Opening the black-box allows in explaining how the model makes the decisions and improves the acceptance of prediction models by the domain experts, as shown in Ref. [20].

### 2.3. Evaluation

A class can be assigned from a probabilistic outcome by assigning a threshold  $D$ , such that event  $c$  is true if  $p(c|x_k) > D$ . The receiver operating characteristic (ROC) curve shows the performance of a two class classifier across the range of possible threshold ( $D$ ) values, plotting one minus the specificity (x-axis) versus the sensitivity (y-axis) [11]. The overall accuracy is given by the area under the curve ( $AUC = \int_0^1 ROCdD$ ), measuring the degree of discrimination that can be obtained from a given model. AUC is a popular classification metric [21] that presents advantages of being independent of the class frequency or specific false positive/negative costs. The ideal method should present an AUC of 1.0, while an AUC of 0.5 denotes a random classifier.

In the domain of marketing, the Lift analysis is popular for accessing the quality of targeting models [3]. Usually, the population is divided into deciles, under a decreasing order of their predictive probability for success. A useful Lift cumulative curve is obtained by plotting the population samples (ordered by the deciles, x-axis) versus the cumulative percentage of real responses captured (y-axis). Similarly to the AUC metric, the ideal method should present an area under the LIFT (ALIFT) cumulative curve close to 1.0. A high ALIFT confirms that the predictive model concentrates responders in the top deciles, while an ALIFT of 0.5 corresponds to the performance of a random baseline.

Given that the training data includes a large number of contacts (51,651), we adopt the popular and fast holdout method (with  $R$  distinct runs) for feature and model selection purposes. Under this holdout scheme, the training data is further divided into training and validation sets by using a random split with 2/3 and 1/3 of the contacts, respectively. The results are aggregated by the average of the  $R$  runs and a Mann-Whitney non-parametric test is used to check statistical significance at the 95% confidence level.

In real environment, the DSS should be regularly updated as new contact data becomes available. Moreover, client propensity to subscribe a bank product may evolve through time (e.g., changes in the economic environment). Hence, for achieving a robust predictive evaluation we adopt the more realistic fixed-size (of length  $W$ ) rolling window evaluation scheme that performs several model updates and discards oldest data [18]. Under this scheme, a training window of  $W$  consecutive contacts is used to fit the model and then we perform predictions related with the next  $K$  contacts. Next, we update (i.e., slide) the training window by replacing the oldest  $K$  contacts with  $K$  newest contacts (related with the previously predicted contacts but now we assume that the outcome result is known), in order to perform new  $K$  predictions, and so on. For a test set of length  $L$ , a total number of model updates (i.e., trainings) are  $U = L/K$ . Fig. 1 exemplifies the rolling window evaluation procedure.

### 2.4. Feature selection

The large number (150) of potential useful features demanded a stricter choice of relevant attributes. Feature selection is often a key DM step, since it is useful to discard irrelevant inputs, leading to simpler data-driven models that are easier to interpret and that tend to provide better predictive performances [12]. In Ref. [34], it is argued that while automatic methods can be useful, the best way is to perform a manual feature selection by using problem domain knowledge, i.e., by having a clear understanding of what the attributes actually mean. In this work, we use a semi-automatic approach for feature selection based on two steps that are described below.

In the first step, business intuitive knowledge was used to define a set of fourteen questions, which represent certain hypotheses that are tested. Each question (or factor of analysis) is defined in terms of a group of related attributes selected from the original set of 150 features by a bank campaign manager (domain expert). For instance, the question about the gender influence (male/female) includes the three features, related with the gender of the banking agent, client and client-agent difference (0 – if same sex; 1 – else). Table 1 exhibits the analyzed factors and the number of attributes related with each factor, covering a total of 69 features (reduction of 46%).

In the second step, an automated selection approach is adopted, based on an adapted forward selection method [12]. Given that standard forward selection is dependent on the sequence of features used and that the features related with a factor of analysis are highly related, we first apply a simple wrapper selection method that works with a



Fig. 1. Schematic of the adopted rolling window evaluation procedure.



**Table 1**  
Analyzed business questions for a successful contact result.

Question (factor of analysis)	Number of features
1: Is offered rate relevant?	5
2: Is gender relevant?	3
3: Is agent experience relevant?	3
4: Are social status and stability relevant?	5
5: Is client–bank relationship relevant?	11
6: Are bank blocks (triggered to prevent certain operations) relevant?	6
7: Is phone call context relevant?	4
8: Are date and time conditions relevant?	3
9: Are bank profiling indicators relevant?	7
10: Are social and economic indicators relevant?	11
11: Are financial assets relevant?	3
12: Is residence district relevant?	1
13: Can age be related to products with longer term periods?	3
14: Are web page hits (for campaigns displayed in bank web sites) relevant?	4
Number of features after business knowledge selection	69
Number of features after first feature selection phase	22

DM fed with combinations of inputs taken from a single factor. The goal is to identify the most interesting factors and features attached to such factors. Using only training set data, several DM models are fit, by using: each individual feature related to a particular question (i.e., one input) to predict the contact result; and all features related with the same question (e.g., 3 inputs for question #2 about gender influence). Let  $AUC_q$  and  $AUC_{q,i}$  denote the AUC values, as measured on the validation set, for the model fed with all inputs related with question  $q$  and only the  $i$ -th individual feature of question  $q$ . We assume that the business hypothesis is confirmed if at least one of the individually tested attributes achieves an  $AUC_{q,i}$  greater than a threshold  $T_1$  and if the model with all question related features returns an  $AUC_q$  greater than another threshold  $T_2$ . When a hypothesis is confirmed, only the  $m$ -th feature is selected if  $AUC_{q,m} > AUC_q$  or  $AUC_q - AUC_{q,m} < T_3$ , where  $AUC_{q,m} = \max(AUC_{q,i})$ . Else, we rank the input relevance of the model with all question related features in order to select the most relevant ones, such that the sum of input importances is higher than a threshold  $T_4$ .

Once a set of confirmed hypotheses and relevant features is achieved, a forward selection method is applied, working on a factor by factor step basis. A DM model that is fed with training set data using as inputs all relevant features of the first confirmed factor and then AUC is computed over the validation set. Then, another DM model is trained with all previous inputs plus the relevant features of the next confirmed factor. If there is an increase in the AUC, then the current factor features are included in the next step DM model, else they are discarded. This procedure ends when all confirmed factors have been tested if they improve the predictive performance in terms of the AUC value.

### 3. Experiments and results

#### 3.1. Modeling

All experiments were performed using the **rminer** package and **R** tool [5] and conducted in a Linux server, with an Intel Xeon 5500 2.27 GHz processor. Each DM model related with this section was executed using a total of  $R = 20$  runs. For the feature selection, we adopted the NN model described in Section 2.2 as the base DM model, since preliminary experiments, using only training data, confirmed that NN provided the best AUC and ALIFT results when compared with other DM methods. Also, these preliminary experiments confirmed that SVM required much more computation when compared with NN, in an expected result since SMO algorithm memory and processing requirements grow much more heavily with the size of the dataset when compared with BFGS algorithm used by the NN. At this stage, we set the number

of hidden nodes using the heuristic  $H = \text{round}(M/2)$  ( $M$  is the number of inputs), which is also adopted by the WEKA tool [34] and tends to provide good classification results [5]. The NN ensemble is composed of  $N_r = 7$  distinct networks, each trained with 100 epochs of the BFGS algorithm.

Before executing the feature selection, we fixed the initial phase thresholds to reasonable values:  $T_1 = 0.60$  and  $T_2 = 0.65$ , two AUC values better than the random baseline of 0.5 and such that  $T_2 > T_1$ ;  $T_3 = 0.01$ , the minimum difference of AUC values; and  $T_4 = 60\%$ , such that the sum of input importances accounts for at least 60% of the influence. Table 1 presents the eight confirmed hypothesis (question numbers in **bold**) and associated result of 22 relevant features, after applying the first feature selection phase. This procedure discarded 6 factors and 47 features, leading to a 32% reduction rate when compared with 69 features set by the business knowledge selection. Then, the forward selection phase was executed. Table 2 presents the respective AUC results (column AUC, average of  $R = 20$  runs) and full list of selected features. The second phase confirmed the relevance of all factors, given that each time a new factor was added, the DM model produced a higher AUC value. An additional experiment was conducted with the LR model, executing the same feature selection method and confirmed the same eight factors of analysis and leading to a similar reduced set (with 24 features). Yet, the NN model with 22 inputs got better AUC and ALIFT values when compared with LR, and thus such 22 inputs are adopted in the remainder of this paper.

After selecting the final set of input features, we compared the performance of the four DM models: LR, DT, NN and SVM. The comparison of SVM with NN was set under similar conditions, where the best hyperparameters ( $H$  and  $\gamma$ ) were set by performing a grid search under the ranges  $H \in \{0, 2, 6, 8, 10, 12\}$  and  $\gamma \in 2^k$ :  $k \in \{-15, -11.4, -7.8, -4.2, -0.6, 3\}$ . The second SVM parameter (which is less relevant) was fixed using the heuristic  $C = 3$  proposed in for **x** standardized input data [5]. The **rminer** package applies this grid search by performing an internal holdout scheme over the training set, in order to select the best hyperparameter ( $H$  or  $\gamma$ ) that corresponds to the lowest AUC value measured on a subset of the training set, and then trains the best model with all training set data.

The obtained results for the modeling phase (using only training and validation set data) are shown in Table 3 in terms of the average (over  $R = 20$  runs) of the AUC and ALIFT metrics (Section 2.3) computed on the validation set. The best result was achieved by the NN model, which outperformed LR (improvement of 3 pp), DT (improvement of 10 pp) and SVM (improvement of 4 and 3 pp) in both metrics and with statistical confidence (i.e., Mann–Whitney  $p$ -value  $< 0.05$ ). In the table, the selected NN and SVM hyperparameters are presented in brackets (median value shown for  $H$  and  $\gamma$ ). It should be noted that the hidden node grid search strategy for NN did not improve the AUC value (0.929) when compared with the  $H = \text{round}(M/2) = 11$  heuristic (used in Table 2). Nevertheless, given that a simpler model was selected (i.e.,  $H = 6$ ), we opt for such model in the remainder of this paper.

To attest the utility of the proposed feature selection approach, we compared it with two alternatives: no selection, which makes use of the all 150 features; and forward selection, which adopts the standard forward method. The latter alternative uses all 150 features as feature candidates. In the first iteration, it selects the feature that produces the highest AUC value, measured using the validation set (1/3 of the training data) when considering the average of 20 runs. Then, the selected feature is fixed and a second iteration is executed to select the second feature within the remaining 149 candidates and the obtained AUC is compared with the one obtained in previous iteration. This method proceeds with more iterations until there is no AUC improvement or if all features are selected. Table 4 compares the three feature selection methods in terms of number of features used by the model, time elapsed and performance metric (AUC).

The obtained results confirm the usefulness of the proposed approach, which obtains the best AUC value. The proposed method uses

**Table 2**  
Final set of selected attributes.

Factor	Attributes	Description	AUC
1: Interest rate	nat.avg.rate suited.rate dif.best.rate.avg	National monthly average of deposit interest rate Most suited rate to the client according to bank criteria Difference between best rate offered and the national average	0.781
2: Gender	ag.sex	Sex of the agent (male/female) that made (outbound) or answered (inbound) the call	0.793
3: agent experience	ag.generic ag.created	If generic agent, i.e. temporary hired, with less experience (yes/no) Number of days since the agent was created	0.799
5: Client–bank relationship	cli.house.loan cli.affluent cli.indiv.credit cli.salary.account	If the client has a house loan contract (yes/no) If the client is an affluent client (yes/no) If the client has an individual credit contract (yes/no) If the client has a salary account (yes/no)	0.805
7: Phone call context	call.dir call.nr.schedules call.prev.durations	Call direction (inbound/outbound) Number of previously scheduled calls during the same campaign Duration of previously scheduled calls (in s)	0.809
8: Date and time	call.month	Month in which the call is made	0.810
9: Bank profiling indicators	cli.sec.group cli.agreggate cli.profile	Security group bank classification If the client has aggregated products and services Generic client profile, considering assets and risk	0.927
10: Social and economic indicators	emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed	Employment variation rate, with a quarterly frequency Monthly average consumer price index Monthly average consumer confidence index Daily three month Euribor rate Quarterly average of the total number of employed citizens	0.929

lesser features (around a factor of 7) when compared with the full feature approach. Also, it is also much faster (around a factor of 5) when compared with the simple forward selection.

### 3.2. Predictive knowledge and potential impact

The best model from previous section (NN fed with 22 features from Table 2, with  $H = 6$  and  $N_r = 7$ ) was tested for its predictive capabilities under a more realistic and robust evaluation scheme. Such scheme is based on a rolling window evaluation (Section 2.3) over the test data, with  $L = 1293$  contacts from the most recent year. Taking into account the computational effort required, the rolling window parameters were fixed to the reasonable values of  $W = 20000$  (window size) and  $K = 10$  (predictions made each model update), which corresponds to  $U = 130$  model updates (trainings and evaluations). We note that a sensitivity analysis was executed over  $W$ , where other  $W$  configurations were tested (e.g., 19,000 and 21,000) leading to very similar results. For comparison purposes, we also tested LR, DT and SVM (as set in Section 3.1).

The results of all  $U = 130$  updates are summarized in Table 5. While a trained model only predicts  $K = 10$  contact outcomes (in each update), the AUC and ALIFT metrics were computing using the full set of predictions and desired values. Similarly to the modeling phase, the best results are given by the NN model and for both metrics, with improvements of: 2.7 pp for SVM, 3.7 pp for DT and 7.9 pp for LR, in terms of AUC; and 1.6 pp for SVM, 2.1 pp for DT and 4.6 pp for LR, in terms of ALIFT. Interestingly, while DT was the worse performing technique in the modeling phase, prediction tests revealed it as the third best model, outperforming LR and justifying the need for technique comparison in every stage of the decision making process [9].

The left of Fig. 2 plots the ROC curves for the four models tested. A good model should offer the best compromise between a desirable high true positive rate (TPR) and low false positive rate (FPR). The former goal corresponds to a sensitive model, while the latter is related with a more specific model. The advantage of the ROC curve is that

the domain user can select the best TPR and FPR trade-off that serves its needs. The NN ROC curve is related with the highest area (AUC) and outperforms all other methods within most (75%) of the FPR range (e.g., NN is the best method for FPR within [0.00,0.10], [0.26,0.85] and [0.94,1.00]).

Focusing on the case studied of bank telemarketing, it is difficult to financially quantify costs, since long term deposits have different amounts, interest rates and subscription periods. Moreover, human agents are hired to accept inbound phone calls, as well as sell other non-deposit products. In addition, it is difficult to estimate intrusiveness of an outbound call (e.g., due to a stressful conversation). Nevertheless, we highlight that current bank context favors more sensitive models: communication costs are contracted in bundle packages, keeping costs low; and more importantly, the 2008 financial crisis strongly increased the pressure for Portuguese banks to increase long term deposits. Hence, for this particular bank it is better to produce more successful sells even if this involves losing some effort in contacting non-buyers. Under such context, NN is the advised modeling technique, producing the best TPR and FPR trade-off within most of the sensitive range. For the range FPR within [0.26,0.85], the NN gets a high TPR value (ranging from 0.75 to 0.97). The NN TPR mean difference under the FPR range [0.45,0.62] is 2 pp when compared with SVM and 9 pp when compared with DT. For demonstrative purposes, the right of Fig. 2 shows the confusion matrix related with the NN model and for  $D = 0.5$ .

The left of Fig. 3 plots the Lift cumulative curves for the predictions using the four models, while the right of Fig. 3 shows examples of cumulative lift response values for the best three models (NN, SVM and DT) and several sample size configurations (e.g., 10% and 50%). Under the cumulative lift analysis, the NN model is the best model within a large portion (77%) of the sample size range. In effect, NN outperforms the SVM model for the sample size ranges of [0.06;0.24] and [0.27;0.99], presenting an average difference of 2 pp within the range [0.27;0.9]. Also, NN is better than DT for the sample size ranges of [0,0.22],

**Table 3**  
Comparison of DM models for the modeling phase (bold denotes the best value).

Metric	LR	DT	SVM ( $\tilde{\gamma} = 2^{-7.8}$ , $C = 3$ )	NN ( $\tilde{H} = 6$ , $N_r = 7$ )
AUC	0.900	0.833	0.891	<b>0.929<sup>a</sup></b>
ALIFT	0.849	0.756	0.844	<b>0.878<sup>a</sup></b>

<sup>a</sup> Statistically significant under a pairwise comparison with SVM, LR and DT.

**Table 4**  
Comparison of feature selection methods for the modeling phase using NN model (bold denotes the best AUC).

Method	#Features	Time elapsed (in s)	AUC metric
no selection	150	3223	0.832
forward selection	7	97,975	0.896
proposed	22	18,651 <sup>a</sup>	<b>0.929</b>

<sup>a</sup> Includes interview with domain expert (5400 s) for Table 1 definition.

**Table 5**

Comparison of models for the rolling window phase (bold denotes the best value).

Metric	LR	DT	SVM	NN
AUC	0.715	0.757	0.767	<b>0.794</b>
ALIFT	0.626	0.651	0.656	<b>0.672</b>

[0.33,0.40], [0.46,0.9] and [0.96,1]. The largest NN difference when compared with DT is achieved for the sample size range of [0.46,0.9], reaching up to 8 pp. Since for this particular bank and context the pressure is set towards getting more successful sells (as previously explained), this is an important sample size range. Currently, the bank uses a standard process that does not filter clients, thus involving a calling to all clients in the database. Nevertheless, in the future there can be changes in the bank client selection policy. For instance, one might imagine the scenario where telemarketing manager is asked to reduce the number of contacts by half (maximum of the bank's current intentions). As shown in Fig. 3, without the data-driven model conceived, telemarketing would reach expectedly just 50% of the possible subscribers, while with the NN model proposed here would allow to reach around 79% of the responses, thus benefiting from an increase of 29 percentage points of successful contacts. This result attests the utility of such model, which allows campaign managers to increase efficiency through cost reduction (less calls made) and still reaching a large portion of successful contacts.

When comparing the best proposed model NN in terms of modeling versus rolling window phases, there is a decrease in performance, with a reduction in AUC from 0.929 to 0.794 and ALIFT from 0.878 to 0.672. However, such reduction was expected since in the modeling phase the feature selection was tuned based on validation set errors, while the best model was then fixed (i.e., 22 inputs and  $H = 6$ ) and tested on completely new unseen and more recent data. Moreover, the obtained AUC and ALIFT values are much better than the random baseline of 50%.

### 3.3. Explanatory knowledge

In this section, we show how explanatory knowledge can be extracted by using a sensitivity analysis and rule extraction techniques (Section 2.2) to open the data-driven model. Using the *Importance* function of the *rminer* package, we applied the Data-based Sensitivity Analysis (DSA) algorithm, which is capable of measuring the global influence of an input, including its interactions with other attributes [7]. The DSA algorithm was executed on the selected NN model, fitted with all training

data (51,651 oldest contacts). Fig. 4 exhibits the respective input importance bar plot (the attribute names are described in more detail in Table 2). A DT was also applied to the output responses of the NN model that was fitted with all training data. We set the DT complexity parameter to 0.001, which allowed us to fit a DT as a low error, obtaining a mean absolute error of 0.03 when predicting the NN responses. A large tree was obtained and to simplify the analysis, Fig. 5 presents the obtained decision rules up to six decision levels. An example of an extracted rule is: if the number of employed is equal or higher than 5088 thousand and duration of previously scheduled calls is less than 13 min and the call is not made in March, April, October or December, and the call is inbound then the probability of success is 0.62. In Fig. 5, decision rules that are aligned with the sensitivity analysis are shown in **bold** and are discussed in the next paragraphs.

An interesting result shown by Fig. 4 is that the three month Euribor rate (euribor3m), computed by the European Central Bank (ECB) and published by Thomson Reuters, i.e., a publicly available and widely used index, was considered the most relevant attribute, with a relative importance around 17%. Next comes the direction of the phone call (inbound versus outbound, 15%), followed by the number of days since the agent login was created, which is an indicator of agent experience in the bank contact center, although not necessarily on the deposit campaign, since each agent can deal with different types of service (e.g., phone banking). The difference between the best possible rate for the product being offered and the national average rate is the fourth most relevant input attribute. This feature was expected to be one of the top attributes, since it stands for what the client will receive for subscribing the bank deposit when compared to the competition. Along with the Euribor rate, these two attributes are the ones from the top five which are not specifically related to call context, so they will be analyzed together further ahead. Last in the top five attributes comes the duration of previous calls that needed to be rescheduled to obtain a final answer by the client. It is also interesting to notice that the top ten attributes found by the sensitivity analysis (Fig. 4) are also used by the extracted decision tree, as shown in Fig. 5.

Concerning the sensitivity analysis input ranking, one may also take into consideration the relevance of the sixth and eighth most relevant attributes, both related to social quarterly indicators of employment, the number of employees and the employment variation rate, which reveal that these social indicators play a role in success contact modeling. While client attributes are specific of an individual, they were considered less relevant, with six of them in the bottom of the input bar plot (Fig. 4). This does not necessarily mean that these types of attributes have general few impact on modeling contact success. In this particular



Fig. 2. ROC curves for the four models (left) and example confusion matrix for NN and  $D = 0.5$  (right).



Fig. 3. Lift cumulative curves for the four models (left) and examples of NN and DT cumulative lift response values (right).

case, the profiling indicators used were defined by the bank and the obtained results suggest that probably these indicators are not adequate for our problem of targeting deposits.

The sensitivity analysis results can also be visualized using a VEC curve, which allows understanding the global influence of an attribute in the predicted outcome by plotting the attribute range of values versus the average sensitivity responses [7]. We analyzed the top five most relevant attributes, with the corresponding VEC curves being plotted in the left (Euribor and product offered interest rates) and right (remaining top 5 relevant attributes) of Fig. 6.

When considering the Euribor rate, one might think that a lower Euribor would result in a decline in savings rate since most European banks align their deposit interest rate offers with ECB indexes, particularly with the three month Euribor [27]. Still, the right of Fig. 6 reveals the opposite, with a lower Euribor corresponding to a higher probability for deposit subscription, and the same probability decreasing along with the increase of the three month Euribor. A similar effect is visible in a decision node of the extracted DT (Fig. 5), where the probability of success decreases by 10 pp when the Euribor rate is higher than 0.73. This

behavior is explained by a more recent research [30], which revealed that while prior to 2008 a weak positive relation could be observed between offered rate for deposits and savings rate, after 2008, with the financial crisis, that relation reversed, turning clients more prone to savings while the Euribor constantly decreased. This apparent contradiction might be due to clients' perception of a real economic recession and social depression. Consumers might feel an increased need to consider saving for the future as opposed to immediate gratification coming from spending money in purchasing desired products or services. This observation emphasizes the inclusion of this kind of information on similar DM projects. Concerning the difference between best product rate offered and national average, Fig. 6 confirms our expectation that an increase in this attribute does increase the probability for subscribing a deposit. Still, once the difference reaches 0.73%, the influence on the probability of subscription is highly reduced, which means that an interest rate slightly above the competition seems to be enough to make the difference on the result. It is also interesting to note that the extracted DT reveals a positive effect of the rate difference with a successful contact (Fig. 5).

The right of Fig. 6 shows the influence of the second, third and fifth most relevant attributes. Regarding call direction, we validate that clients contacted through inbound are keener to subscribe the deposit. A similar effect is measured by the extracted DT, where an inbound call increases the probability of success by 25 pp (Fig. 5). Inbound is associated with less intrusiveness given that the client has called the bank and thus he/she is more receptive for a sell. Another expected outcome is related with agent experience, where the knowledge extraction results show that it has a significant impact on a successful contact. Quite interestingly, a few days of experience are enough to produce a strong impact, given that under the VEC analysis with just six days the average probability of success is above 50% (Fig. 6) and the extracted DT increases the probability of successful sell by 9 pp when the experience is higher or equal than 3.3 days (Fig. 5). Regarding the duration of previously scheduled calls, it happens often that the client does not decide on the first call on whether to subscribe or not the deposit, asking to be called again, thus rescheduling another call. In those cases (63.8% for the whole dataset), a contact develops through more than one phone call. The sensitivity analysis (Fig. 6) shows that more time already spent on past calls within the same campaign increases probability of success. Similarly, the extracted DT confirms a positive effect of the duration of previous calls. For instance, when the duration is higher or equal than 13 min (left node at the second level of Fig. 5), then the associated global probability of success is 0.3, while the value decreases to 0.05 (25 pp difference) if this duration condition is false.



Fig. 4. Relative importance of each input attribute for the NN model (in %).





Fig. 5. Decision tree extracted from the NN model.

It is interesting to note that some explanatory variables are uncontrolled by the commercial bank (e.g., three month Euribor rate) while others are partially controlled, i.e., can be influenced by bank managers' decisions (e.g., difference between best offered and national average rates, which also depends on competitors' decisions), and other variables can be fully controlled (e.g., direction of call, if outbound; agent experience — ag.created; duration of previously scheduled calls). Given these characteristics, telemarketing managers can act directly over some variables, while analyzing expectations influenced by uncontrolled variables. For instance, managers can increase campaign investment (e.g., by assigning more agents) when the expected return is high, while postponing or reducing marketing campaigns when a lower success is globally predicted.

#### 4. Conclusions

Within the banking industry, optimizing targeting for telemarketing is a key issue, under a growing pressure to increase profits and reduce costs. The recent 2008 financial crisis dramatically changed the business of European banks. In particular, Portuguese banks were pressured to increase capital requirements (e.g., by capturing more long term deposits). Under this context, the use of a decision support system (DSS) based on a data-driven model to predict the result of a telemarketing phone call to sell long term deposits is a valuable tool to support client selection decisions of bank campaign managers.

In this study, we propose a personal and intelligent DSS that uses a data mining (DM) approach for the selection of bank telemarketing clients. We analyzed a recent and large Portuguese bank dataset, collected from 2008 to 2013, with a total of 52,944 records. The goal was to model the success of subscribing a long-term deposit using attributes that were known before the telemarketing call was executed. A particular emphasis was given on feature engineering, as we considered an initial set of 150 input attributes, including the commonly used bank client and product features and also newly proposed social and economic indicators. During the modeling phase, and using a semi-automated feature selection procedure, we selected a reduced set of 22 relevant features. Also, four DM models were compared: logistic regression (LR), decision trees (DTs), neural networks (NNs) and support vector machines (SVMs). These models were compared using two metrics, area of the receiver operating characteristic curve (AUC) and area of the LIFT cumulative curve (ALIFT), both at the modeling and rolling window evaluation phases. For both metrics and phases, the best results were obtained by the NN, which resulted in an AUC of 0.80 and ALIFT of 0.67 during the rolling window evaluation. Such AUC corresponds to a very good discrimination. Moreover, the proposed model has impact in the banking domain. For instance, the cumulative LIFT analysis reveals that 79% of the successful sells can be achieved when contacting only half of the clients, which translates in an improvement of 29 percentage points when compared with the current bank practice, which simply contacts all clients. By selecting only the most likely buyers, the proposed DSS creates value for the bank telemarketing managers in



Fig. 6. VEC curves showing the influence of the first and fourth (left) and second, third and fifth (right) most relevant attributes.



terms of campaign efficiency improvement (e.g., reducing client intrusiveness and contact costs).

Two knowledge extraction techniques were also applied to the proposed model: a sensitivity analysis, which ranked the input attributes and showed the average effect of the most relevant features in the NN responses; and a decision tree, which learned the NN responses with a low error and allowed the extraction of decision rules that are easy to interpret. As an interesting outcome, the three month Euribor rate was considered the most relevant attribute by the sensitivity analysis, followed by the direction call (outbound or inbound), the bank agent experience, difference between the best possible rate for the product being offered and the national average rate, and the duration of previous calls that needed to be rescheduled to obtain a final answer by the client. Several of the extracted decision rules were aligned with the sensitivity analysis results and make use of the top ten attributes ranked by the sensitivity analysis. The obtained results are credible for the banking domain and provide valuable knowledge for the telemarketing campaign manager. For instance, we confirm the result of Ref. [30], which claims that the financial crisis changed the way the Euribor affects savings rate, turning clients more likely to perform savings while Euribor decreased. Moreover, inbound calls and an increase in other highly relevant attributes (i.e., difference in best possible rate, agent experience or duration of previous calls) enhance the probability for a successful deposit sell.

In future work, we intend to address the prediction of other telemarketing relevant variables, such as the duration of the call (which highly affects the probability of a successful contact [23]) or the amount that is deposited in the bank. Additionally, the dataset may provide history telemarketing behavior for cases when clients have previously been contacted. Such information could be used to enrich the dataset (e.g., computing recency, frequency and monetary features) and possibly provide new valuable knowledge to improve model accuracy. Also it would be interesting to consider the possibility of splitting the sample according to two sub-periods of time within the range of 2008–2012, which would allow us to analyze impact of hard-hit recession versus slow recovery.

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**Sérgio Moro** holds a 5 year degree diploma in Computer Engineering from Instituto Superior Técnico (Technical University of Lisbon), and a MSc in Management Information Systems from ISCTE – University Institute of Lisbon, where he is also a PhD researcher in the fields of business intelligence and decision support systems. He currently works in the Business Intelligence & Analytics team of a Portuguese bank, where he is responsible for projects such as GRC (Governance, Risk and Compliance), and ALM (Asset–Liability Management). Previously he was responsible for software development for the bank's contact center.



**Paulo Cortez** is an Associate Professor at the Department of Information Systems at University of Minho and Coordinator of the Information Systems and Technologies R&D group of ALGORITMI Research Centre. He completed his PhD (2002) in Computer Science and Habilitation (2013) in Information Systems and Technologies at the same university. His research interests include: business intelligence, data mining, neural networks, evolutionary computation and forecasting. Currently, he is associate editor of the journals *Expert Systems and Neural Processing Letters*. He has published more than 92 indexed (ISI or Scopus) papers. His research has appeared in *Journal of Heuristics*, *Decision Support Systems*, *Information Sciences* and others (see <http://www3.dsi.uminho.pt/pcortez>).



**Paulo Rita** holds a PhD in Marketing from Cardiff Business School, UK and has a Post-Doctorate in E-Marketing from the University of Nevada Las Vegas, United States. Dr Rita is Professor of Marketing at IBS – ISCTE Business School, Lisbon – Portugal where he is Director of the PhD in Marketing, Director of the PhD in Tourism Management in partnership with the European University and Director of the Master in Hospitality and Tourism Management which is a double degree with University of Central Florida, Orlando, United States. Paulo Rita is currently a member of the Executive Committee of EMAC (European Marketing Academy) and Vice President of EDAMBA (European Doctoral Programmes Association in Management and Business Administration).

His areas of scientific research interest and expertise are in Consumer Behavior, E-Marketing, Business Intelligence/Analytics and Tourism Marketing.