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| **Bank Marketing Campaign Classification** |

**Group 8**

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**Abstract**

Using dataset from Portuguese banking institution from May 2008 to November 2010, we applied various machine learning classification methods to predict the effectiveness of the bank direct campaigns (by phone calls) to get potential customers to subscribe to term deposit. By comparing Type-II error (False Negative Rate), we found that Random Forest yielded best prediction.

**1 Introduction**

Banks regularly conduct direct marketing campaigns to get the potential customers to subscribe to certain products. It is therefore important to analyse the dataset to predict the effectiveness of direct marketing campaign.

**2 Objective**

The classification goal is to predict if the direct marketing campaign is effective to get the potential customers will subscribe to a bank product.

For this project, the direct marketing campaign is done by phone calls and the bank product is term deposit.

**3 Dataset**

All the analysis is done in R, files saved as R Markdown (.Rmd).

This dataset is based on "Bank Marketing" UCI dataset ‘bank-additional-full.csv’ containing 41188 number of instances. There are 20 + output attribute, the binary classification goal is to predict if the client will subscribe a bank term deposit (variable y).

Detail descriptions of each variables can be found in Appendix A.

**4 Methodologies**

There are several machine learning techniques employed for comparison:

* K-nearest neighbours (KNN)
* Logistic Regression
* Decision tree
* Random Forest
* Gradient Boosting
* Adaptive Boosting (AdaBoost)
* Extreme Gradient Boosting (XGboost)
* Support Vector Machine (SVM) with linear kernel
* Support Vector Machine (SVM) with polynomial kernel
* Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel

**5 Pre-processing and Exploratory Analysis**

**5.1 Pre-processing**

This dataset comprises of a significant amount of missing data which was indicated by “unknown” values. For instance, from the 41188 data points in the “default” column, there were 8597 “unknown” values, 1731 in “education”, 990 in “housing” and “loan”, 330 in “job”, and 80 in “marital”. The details of how we deal with the missing values are shown in the next section.

We did further data pre-processing to deal with the missing values as well as to reduce the amount of noise in our dataset. As our dataset was hugely imbalanced with 88% of respondents saying “no” and only 12% saying “yes”, we also did oversampling, which helped to reduce the type II error that we were interested in as it helped our model better generalise for the “yes” values we wanted to characterise.

**5.2 Exploratory Analysis**

In the “default” column, the fields filled with “unknown” values had 32588 “no”, 8597 “unknown”, and 3 “yes”. Inside “default’s “no’s, there were 87.1% that eventually said no to the bank for the marketing campaign, which is lower than 94.8% in the respondents that had unknown values. As all the yes in default replied no to the marketing campaign, the unknown and yes values were re-coded to be the same in the dataset.

For education’s unknown values, the behaviour of the unknown values was assessed, finding that they are most similar to that of university students, as can be seen from our code, and therefore recoded them to be university students as well.

The “housing” and “loan” columns were found to be statistically insignificant, from a chi-squared analysis and were dropped from the dataset to reduce noise in the dataset, which seemed to improve the results.

Unknown values in “job” was found to have distinct composition of result to the marketing campaign, and hence were re-labelled as unconventional.

From reading the description of some of the fields, we found that variables ‘poutcome’ and ‘previous’ seemed to be characterising similar information. Hence it seemed to be a good idea to merge this fields to output a single column. Failures were given a weight of 0.5, non-existent = 0.2, and success given 1. These weights were then used to multiply against “previous” +1. We added 1 as we did not want to multiple any values with 0. The 2 original columns were then dropped.

Age in this dataset was particularly interesting. We noticed that the proportion of people that said yes to the marketing campaign decreased with age, except that trend became significantly different after 60, where many began to reply yes and the trend with age seemed random. Re-categorised age into 7 values, for whichever age group the individual was in to reduce noise, and those over the age of 51 would be in one group. The histograms and other exploratory analysis visualisations can be found in Appendix B.

**6 Findings**

Because of the highly imbalance data (only 12% said Yes to term deposit), any classification models will classify label as ‘No’ so much more than ‘Yes’, therefore resulting in very good accuracy or low classification error rate.

However, looking more closely to the problem, Bank would not want to miscategorise potential customers that will say ‘Yes’ as ‘No’. In other words, Bank are more likely to be concerned on reducing the number of **False Negative** – the number of customers identified as saying ‘No’ but in fact would have said ‘Yes’.

Therefore, in order to choose the best prediction models, the False Negative Rate or type-II errors are compared instead of misclassification accuracy rate.

In addition to looking at type-II errors, we also want to know if we can reduce the **False Positive** – the number of customers identified as saying ‘Yes’ but in fact would have said ‘No’.

**Receiver Operating Characteristic (ROC)** curves are created to illustrate both error types for all possible probability of prediction occurrence (threshold). The x-axis on ROC curve shows the **False Positive Rate** / type-I error and the y-axis shows the **True Positive Rate** / 1 – type II error (also called recall or sensitivity).

For binary classification like this project, the prediction is ‘Yes’ if the probability is more than 0.5 (threshold = 0.5). Since Bank might be more concerned of not missing customers that will say ‘Yes’, we can reduce the threshold from 0.5 to smaller number like 0.3 or 0.2.

As the threshold is reduced, the False Negative Rate/type-II error will be reduced (True Positive Rate in y-axis increases). However, at the same time, False Positive Rate / type-I error in x-axis will increase.

So which threshold is the best and should be chosen? Unfortunately, there is no easy answer to this.

Domain knowledge is required to choose the threshold. For example: Bank needs to calculate the cost of performing more marketing campaign for more potential customer and compare it with the actual profit for each actual term deposit signup.

In addition to showing the trade-off between type-I and type-II errors, ROC curves can also be used to indicate the overall performance of classification over all possible thresholds. This is given by Area Under ROC Curve or AUC.

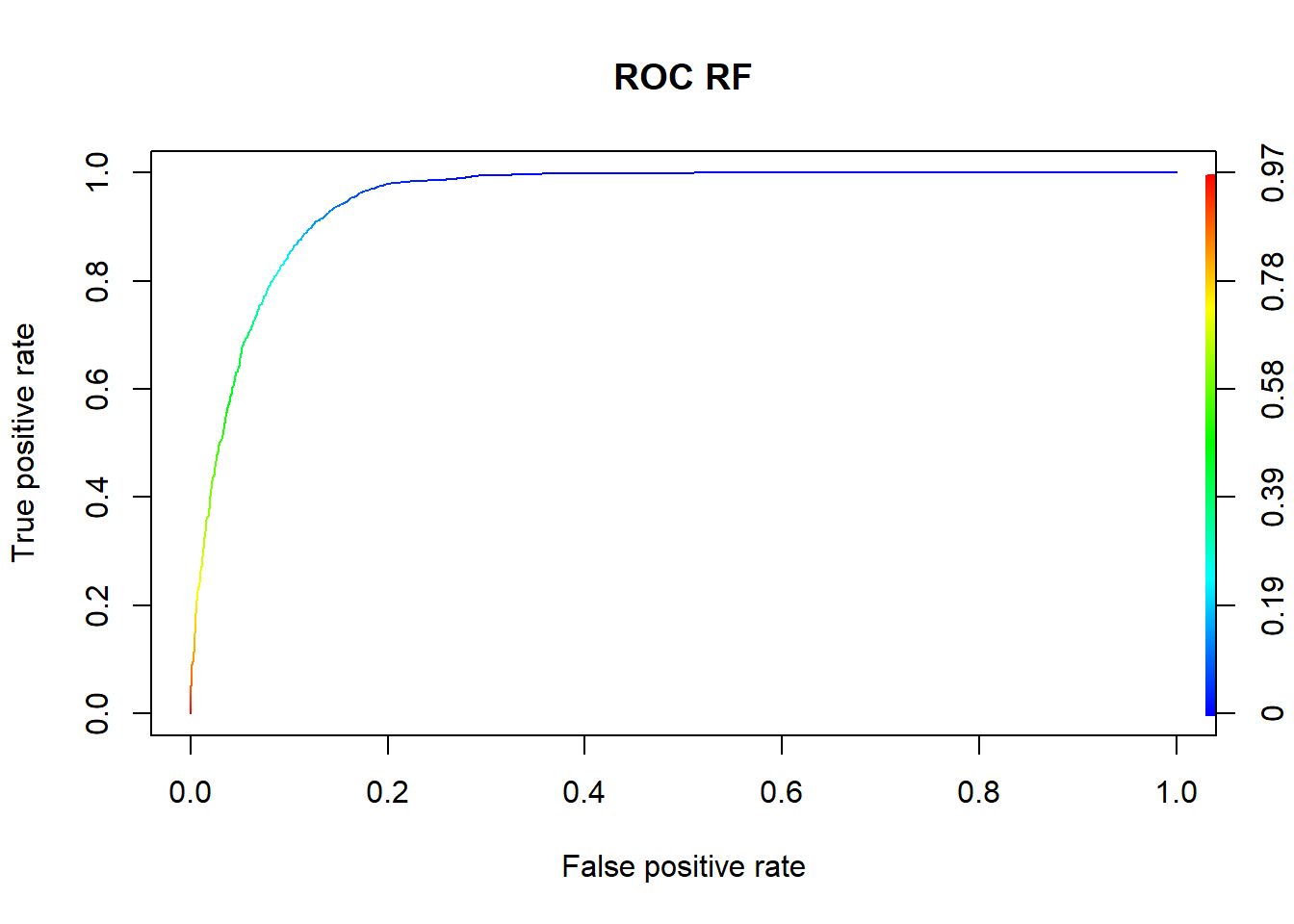
**6.1 Classification Results**

The following table summarizes classification results:

Table 6-1: Classification Result

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Misclass error** | **Type-II error** | **Precision** | **Recall** |
| KNN | 0.0920 | 0.5240 | 0.6255 | 0.4760 |
| Logistic regression | 0.0893 | 0.5827 | 0.6730 | 0.4173 |
| Decision tree | 0.0932 | 0.6531 | 0.6757 | 0.3469 |
| **Random forest** | 0.0827 | **0.4482** | 0.6645 | 0.5518 |
| Gradient boosting | 0.0819 | 0.4578 | 0.6737 | 0.5422 |
| Adaboost | 0.0895 | 0.4632 | 0.6241 | 0.5368 |
| XGBoost | 0.0816 | 0.4568 | 0.676 | 0.5432 |
| SVM (linear kernel) | 0.0972 | 0.6894 | 0.6525 | 0.3106 |
| SVM (polynomial kernel) | 0.0944 | 0.7375 | 0.7387 | 0.2625 |
| SVM (RBF kernel) | 0.0915 | 0.6553 | 0.6976 | 0.3447 |

Figure 6-1: Random Forest ROC Curve (**AUC = 0.951**)



From the table, Random Forest has the best classification result (lowest type-II error). Please find our R codes in Appendix C for further details.

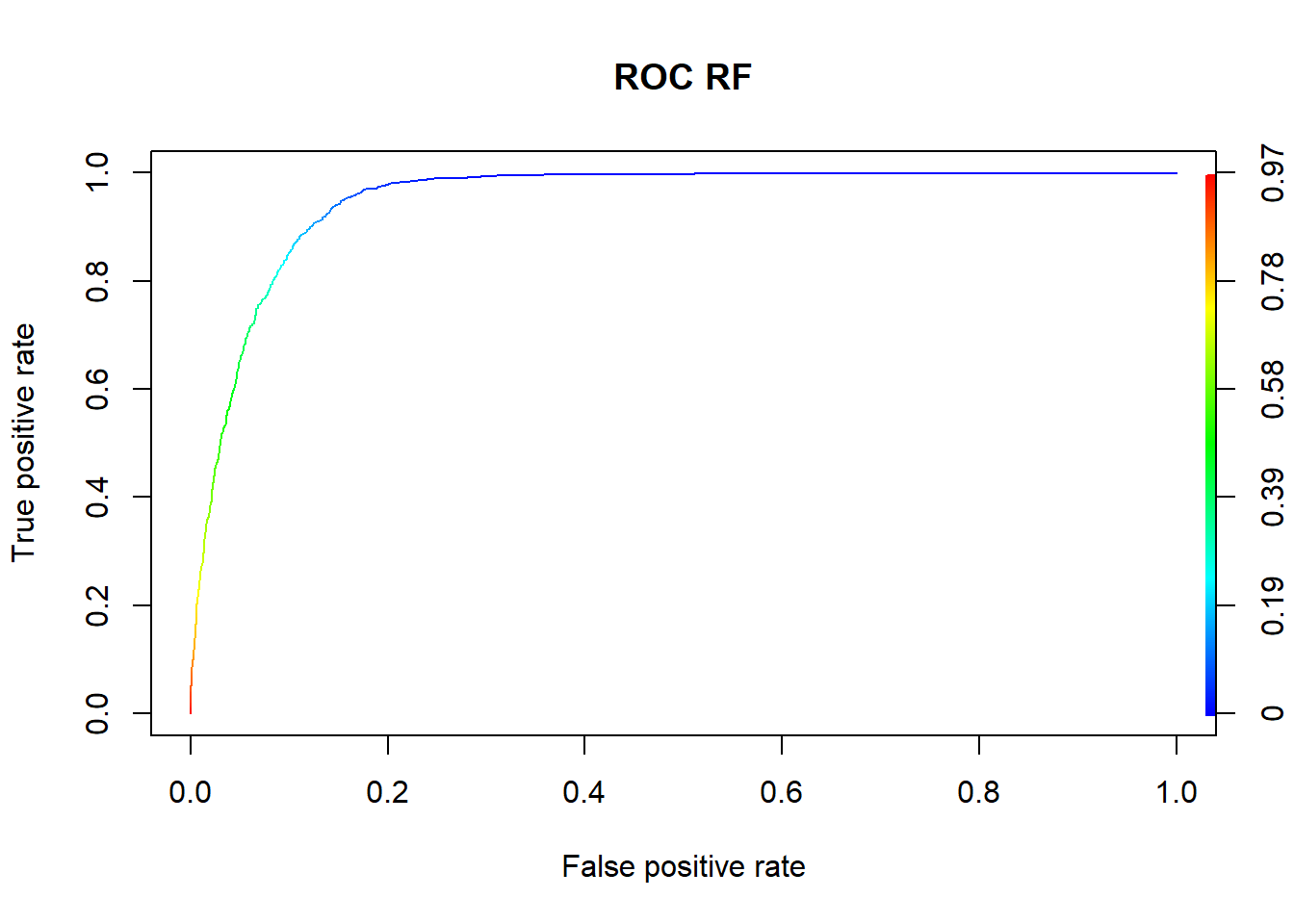
**6.2 Classification with Scaled Numerical Variables Results**

The following table summarizes classification results:

Table 6-2: Classification Results (Scaled Numerical Variables)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Misclass error** | **Type-II error** | **Precision** | **Recall** |
| KNN | 0.0906 | 0.5560 | 0.6490 | 0.4440 |
| Logistic regression | 0.0893 | 0.5827 | 0.6730 | 0.4173 |
| Decision tree | 0.0932 | 0.6531 | 0.6757 | 0.3469 |
| Random forest | 0.0839 | **0.4536** | 0.6581 | 0.5464 |
| Gradient boosting | 0.0819 | 0.4578 | 0.6737 | 0.5422 |
| Adaboost | 0.0896 | 0.4642 | 0.6236 | 0.5358 |
| XGBoost | 0.0816 | 0.4568 | 0.6760 | 0.5432 |
| SVM (linear kernel) | 0.0972 | 0.6894 | 0.6525 | 0.3106 |
| SVM (polynomial kernel) | 0.0944 | 0.7375 | 0.7387 | 0.2625 |
| SVM (RBF kernel) | 0.0915 | 0.6553 | 0.6976 | 0.3447 |

Figure 6-2: Random Forest ROC Curve (**AUC = 0.951**)



There is slight improvement / reduction on type-II errors, but generally scaling the numerical variables do not have any significant effect to the classification results. Please find our R codes in Appendix D for further details.

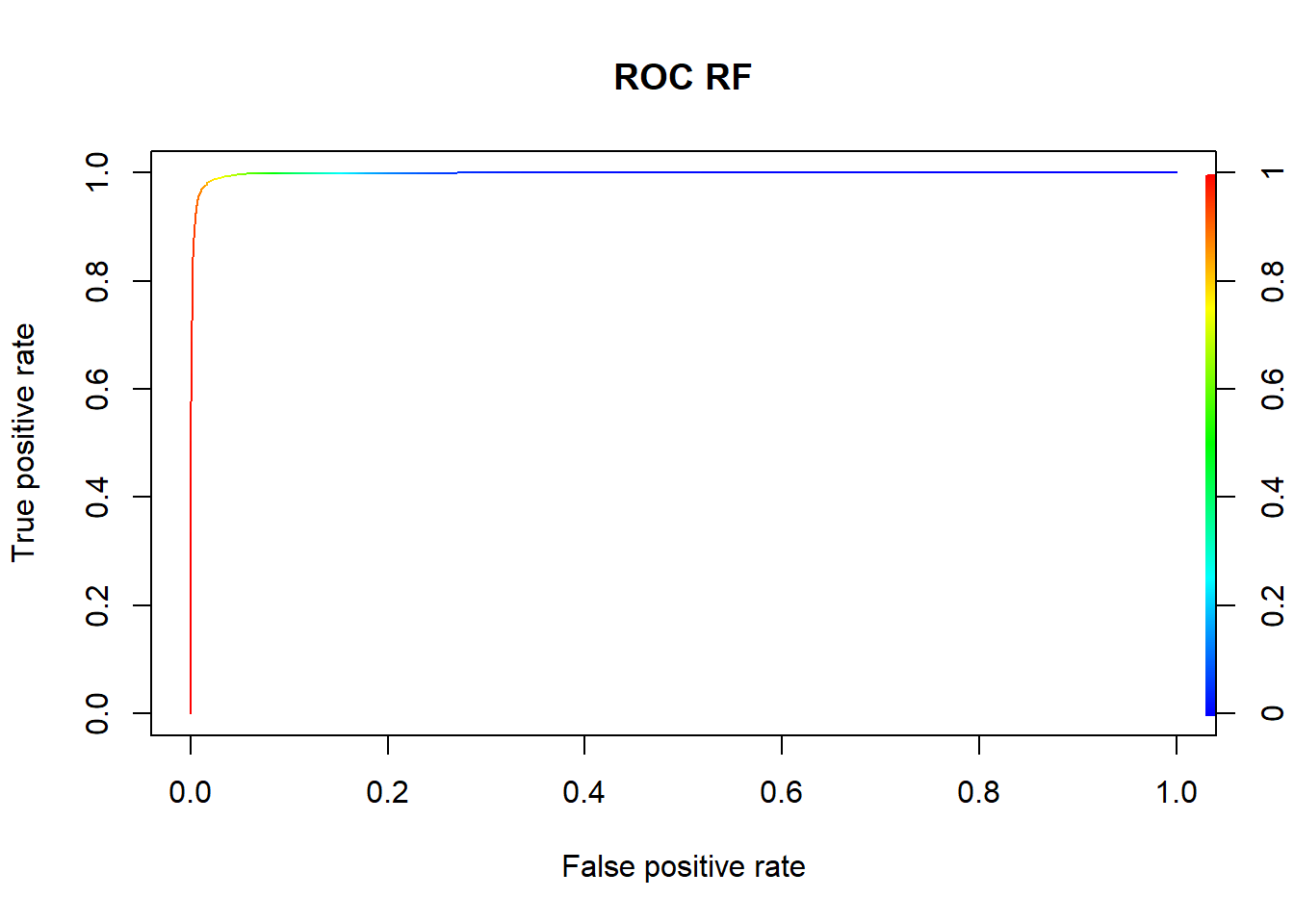
**6.3 Classification with Oversampling Variables Results**

The following table summarizes classification results:

Table 6-3: Classification Results (with Oversampling)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Misclass error** | **Type-II error** | **Precision** | **Recall** |
| KNN | 0.0900 | 0.0106 | 0.8544 | 0.9894 |
| Logistic regression | 0.1249 | 0.1103 | 0.8654 | 0.8897 |
| Decision tree | 0.2064 | 0.0598 | 0.7281 | 0.9402 |
| Random forest | 0.0422 | **0.0015** | 0.9236 | 0.9985 |
| Gradient boosting | 0.1064 | 0.0655 | 0.8646 | 0.9345 |
| Adaboost | 0.0879 | 0.0489 | 0.8829 | 0.9511 |
| XGBoost | 0.0981 | 0.0504 | 0.8676 | 0.9496 |
| SVM (linear kernel) | 0.1187 | 0.0832 | 0.8569 | 0.9168 |
| SVM (polynomial kernel) | 0.1211 | 0.0891 | 0.8569 | 0.9109 |
| SVM (RBF kernel) | 0.1113 | 0.0598 | 0.8532 | 0.9402 |

Figure 6-3: Random Forest ROC Curve (**AUC = 0.998**)



Oversampling significantly reduces type-II error in Random Forest. Please find our R codes in Appendix E for further details.

**6.4 Variables Importance**

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| --- | --- | --- |
|  |  |  |

Figure 6-4: Random Forest Variables Importance

Duration call is self-explanatory: the longer the call being made, the more likely that potential customers will subscribe to term deposit.

Euribor is short for Euro Interbank Offered Rate, which is the average interest rates at which a large panel of European banks borrow funds from one another (equivalent to SIBOR –Singapore Interbank Offered Rate in Singapore). The Euribor rates are the reference rates in the European money market, to be used as basis for the price and interest rates of all kinds of financial products like interest rate swaps, interest rate futures, saving accounts and mortgages.

Therefore, it makes sense that more potential customer will subscribe to term deposit when the interest rate (based on Euribor rate) is higher.

**7 Lesson Learnt**

In order to assess the effectiveness of this direct marketing campaigns by phone calls of the banking institution, we have worked on the prediction on if the client will subscribe a term deposit (variable y) with the use of different models with and without scaled numerical variables and oversampling. In our evaluation of the features, we can say that the top feature is "Duration" due to its high correlation to Y. In real life situation, if duration of call is longer, it’s a strong indication of interest, thus higher chance of subscription. We have taken necessary steps for the data pre-processing and presented the results comparison and justify our selection of model. For all results we run out, we have shown results of Random forest has the higher ability of distinguishing with the maximum AUC of more than 0.95.

We have learnt ROC curve serves as a good performance measurement for classification problem at various threshold settings. ROC is a probability curve and AUC represent degree or measure of separability. Higher the AUC, better the model is at predicting YES as YES and NO as NO. By analogy, Higher the AUC, better the model is at distinguishing between customers who are willing or willing not to subscribe the term deposit. That is how we rationalise our selection of model.

We have also used Type I and Type II errors to analysis the model, the formula has been shown in the R codes. False Positive, or the Type I error means the client does not subscribe to term deposit, but the model thinks he/she does. False Negative, or the Type II error means the client subscribes to term deposit, but the model said he/she does not. In fact, for banks, false positive means the rate when banks think that they have the client but actually they have lost them. We will not think that this is something the bank is interested to know in the sense that banks are more revenue focusing. Then Type II error should be the one we are focusing on. We have actually predicted that the tree-based methods, especially Random Forest will have the lowest type-II errors since we have learnt in lectures that tree-based methods is the best for categorical variables, which we have quite a number of them for our dataset,

There are quite a number of difficulties and challenges in our project. One big challenge is that most features are categorical and there are quite a number of unknowns. Which we have attempted to solve the problem at the beginning. Another challenge we met is the hardware limitation to process large set of data, we have spent quite a long time to get the error results for certain models, e.g. KNN.

**References**

[1] S. Moro, P. Cortez and P. Rita (2014) A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014

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[3] <https://github.com/z-o-e/bank_data_analysis/blob/master/Linear_Models_Discriminants_Additive_Models_trees.R>

[4] <https://www.kaggle.com/janiobachmann/bank-marketing-campaign-opening-a-term-deposit>

[5] <https://www.kaggle.com/psqrtpsqrt/bank-marketing-eda-classification-pr-f-score#model-selection>