Project Proposal

Review Phase #1

DAB103 – Section 4

November 12, 2021

ST. CLAIR COLLEGE

ZEKELMAN SCHOOL OF BUSINESS & INFORMATION TECHNOLOGY

Project Proposal

Phase#1

ST. CLAIR COLLEGE

Course	Analytic Tools and Decision Making
Course Code	DAB 103
Section No.	004
Academic Term	Fall 2021
Professor	Mr. Sathish Chandra Pichika

ZEKELMAN SCHOOL OF BUSINESS & INFORMATION TECHNOLOGY

Team Introduction

Group Name	INSIGHT




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Education Background	MBA	Industrial Eng.	B.S. Computer Application	B.S. Computer Application
Previous Experience	Marketing Manager	Biz. Development Manager	Student	Student

Dataset Description

- About Dataset
- Dataset Characteristic
- Other Works on this Dataset

About Dataset

Title	Bank Marketing Data
Source	Data.world
Dataset	https://data.world/data-society/bank-marketing-data http://archive.ics.uci.edu/ml/datasets/Bank+Marketing
Data Link	https://query.data.world/s/lqrsaugj7kwkyazkvydowjuxjrybxx
Description	The data is related with direct marketing campaigns (phone calls) of a Portuguese banking institution.
Main Article	Moro et al., 2014, S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014

About Dataset

There are four datasets extracted from Main Dataset used in the article:

- bank-additional-full.csv with all examples (41188) and 20 inputs, ordered by date (from May 2008 to November 2010), very close to the data analyzed in [Moro et al., 2014]
- bank-additional.csv with 10% of the examples (4119), randomly selected from 1), and 20 inputs.
- bank-full.csv with all examples and 17 inputs, ordered by date (older version of this dataset with less inputs).
- bank.csv with 10% of the examples 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).

The classification goal was to predict if the client will subscribe (yes/no) a term deposit (variable y).

Dataset Characteristic

- The data is related with direct marketing campaigns of a **Portuguese banking institution**.
- The marketing campaigns were based on **phone calls**.
- Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be **('yes') or not ('no')** subscribed.
- The data is example of data very close to the data analyzed in the main article ordered by date from **May 2008 to November 2010**.

Other Works on this Dataset

Classification

: https://github.com/mcabinaya/Bank-Marketing-Data-Analysis

Predict Subscription

: https://medium.com/swlh/using-machine-learning-to-predict-subscription-to-bank-term-deposits-for-clients-with-python-aec8a4690807

Machine Learning

: https://rpubs.com/alfandash/lbb-classification-2

Background & Motivation

- Industry Knowledge domain
- The Telemarketing Main Problems
- Background & Motivation

Industry Knowledge domain

Investopedia

Telemarketing is **the direct marketing of goods or services to potential customers over the telephone or the Internet**.

Four common kinds of telemarketing include outbound calls, inbound calls, lead generation, and sales calls.

Industry Knowledge domain

Financial telemarketers convince consumers to switch banks or their stock trading account by making those necessary telemarketing calls.

- Bank is one of the organization use telemarketing method for selling banking products or services.
- Telemarketing is a popular method used by bank to selling, because bank products and services sometimes too complicated for some users to understand.

The Telemarketing Main Problems

As much as we are crazy for telemarketing, we cannot ignore the persistent problems facing it today!

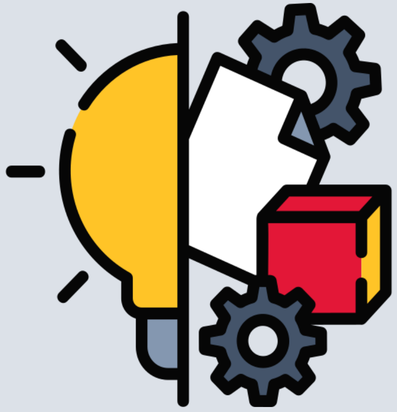
Rejections

B2B marketers are getting rejected as more people have cynical whenever they receive a telemarketer

Increased costs

The Companies cannot initiate a cold calling campaign without churning out a hefty sum of money

Background & Motivation



Background & Motivation

- A good telemarketing campaign plan clearly outlines the details and the scope of the campaign, so everyone is clear about what it involves and how it'll work.
- Telemarketing campaigns can help you reach a group of targeted prospects or customers to communicate a message, gather feedback, and determine a next step for the relationship.

Problem Statement Project Proposal &

- Problem Statement
- Project Proposal
- Project Audience
- Short Problem Statement
- Analysis Questions

Problem Statement

Marketing strategy could evolve over time. As the bank learn more about what is and what is not working, it will build a deeper understanding of the marketplace. Building an effective campaign strategy can help bank and its marketing department to create the better positioning for understanding the customers requirements.

Benefits of effective Marketing Campaigns

- Attracts more sales
- Improve the reputation of the bank
- Improve Undertesting of the market & customers
- Better long-term marketing campaigns

Project Proposal

The product of this project will be a descriptive analytics that examines the characteristics of a successful phone call for the purpose of direct marketing in terms of targeted prospect customers and properties of the call session, based on the data set.

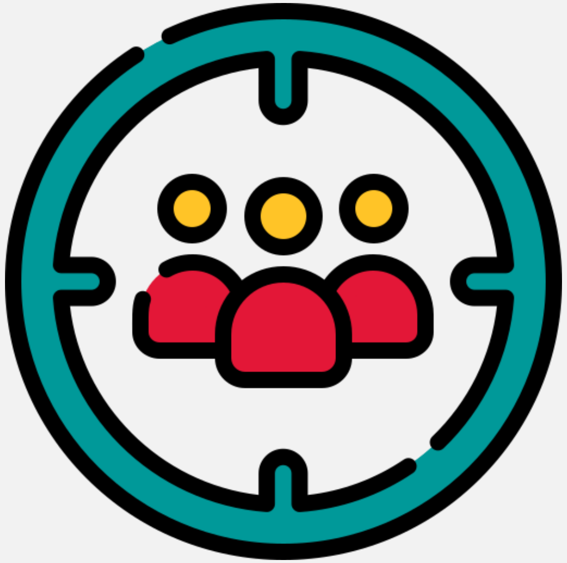
The output of this project may help marketing managers in similar industries (e.g. finance, other service industries) to improve the performance of their direct marketing efforts by increasing the efficiency and effectiveness of the phone calls by exploring some of the aspects of successful direct marketing calls recorded in the dataset.

Proposal Statement

Project Audience

Audiences

- Marketing Department
- Medium & High-level Managers
- Sales Department
- Call Centers



Short Problem Statement

Problem Statement

How to increase effectiveness of direct marketing campaign based on the dataset

Analysis Questions

Question

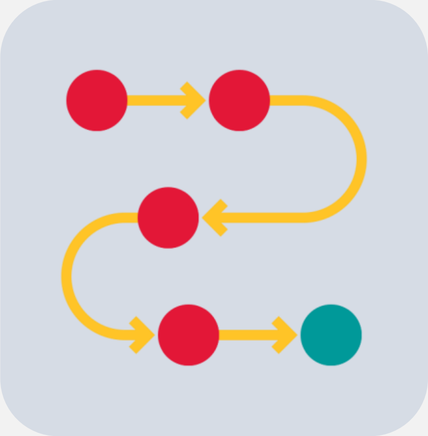
- Who are the top targeted prospects in terms of successful outcome?
- What is the best time to contact prospect customers?
- What are the top characteristics of a successful call (duration and time)?

Preliminary Exploratory Data Analysis (EDA)

- Data Description
- Univariant Preliminary Visualization: Numeric Variables
- Univariant Preliminary Visualization: Categorical Variables
- Future Exploration & Expected Transformation Steps

Preliminary EDA Steps

In this chapter, for the initial EDA:



- The data types of variables will be explored
- Each variable will be introduced
- A plot and short description of each variable will be discussed.
- A general exploration of correlation among numerical variables will be provided

Data Description

To describe and analyze the data, we need to understand the nature of data.

The type of statistical analysis is influenced by the type of data and can be performed on it.

DataFrame Structure

Primary Dataset Structure

No. Variables	21
No. Rows	41188

New-Structured Dataset

No. Variables	16
No. Rows	41188

Social and Economic context Attributes that have been Eliminated based on Problem statement

Name	Description	Data Type
emp.var.rate	employment variation rate - quarterly indicator	Numeric
cons.price.idx	consumer price index - monthly indicator	Numeric
cons.conf.idx	consumer confidence index - monthly indicator	Numeric
euribor3m	euribor 3 month rate - daily indicator	Numeric
nr.employed	number of employees - quarterly indicator	Numeric

Variables: Type & Description

Old Name	New Name	Data Type	Description
age	Age	Numeric	Client Age in Year
job	Job	Categorical	Client's Job type (admin, bluecollar, housemaid, management, retired, self-employed, services, student, technician, unemployed, unknown)
marital	Marital	Categorical	Marital status (divorced (divorced or widowed), married , single, unknown)
education	Education	Categorical	Level of education (basic.4y, basic.6y, basic.9y, high.school, illiterate, professional.course, university.degree, unknown)
default	Credit	Categorical	Has the client credit in default? (no , yes, unknown)
housing	Housing_loan	Categorical	Has the client housing loan? (no , yes, unknown)
loan	Personal_loan	Categorical	Has the client personal loan? (no , yes, unknown)
contact	Call_type	Categorical	Type of contact communication (cellular, telephone)
month	Last_month	Categorical	Last contact month of year (jan, feb, mar, apr, .., nov, dec)
day_of_week	Last_weekday	Categorical	Last contact day of the week (mon, tue, wed, thu, fri)
duration	LastCall_Dur	Numeric	Last contact duration, in seconds. The duration is not known before a call is performed. (if LastCall_Dur=0 then y='no')
campaign	NewCampaign_CallNo	Numeric	Number of contacts performed during this campaign and for this client
pdays	Campaign_Intervals_Day	Numeric	Number of days passed by after the client was last contacted from a previous campaign
previous	PrevCampaign_CallNo	Numeric	Number of contacts performed before this campaign and for this client
poutcome	PrevCampaign_Result	Categorical	Outcome of the previous marketing campaign (failure, nonexistent, success)
y	Campaign_Success	Categorical	Has the client subscribed a term deposit? (binary: yes , no)

Data Type

Categorical

- Job
- Education
- Marital
- Credit
- Personal_loan
- Housing_loan
- Last_month
- Last_weekday
- PrevCampaign_Result
- Call_type
- Campaign_Success

Numerical

- Age
- LastCall_Dur
- NewCampaign_CallNo
- PrevCampaign_CallNo
- Campaign_Intervals_Day

Missing & Unknown Values

"Unknown" Values		
Job	330	% 0.8
Marital	80	% 0.19
Education	1731	% 4.2
Credit	8597	% 20.9
Housing_Loan	990	% 2.4
Personal_Loan	990	% 2.4

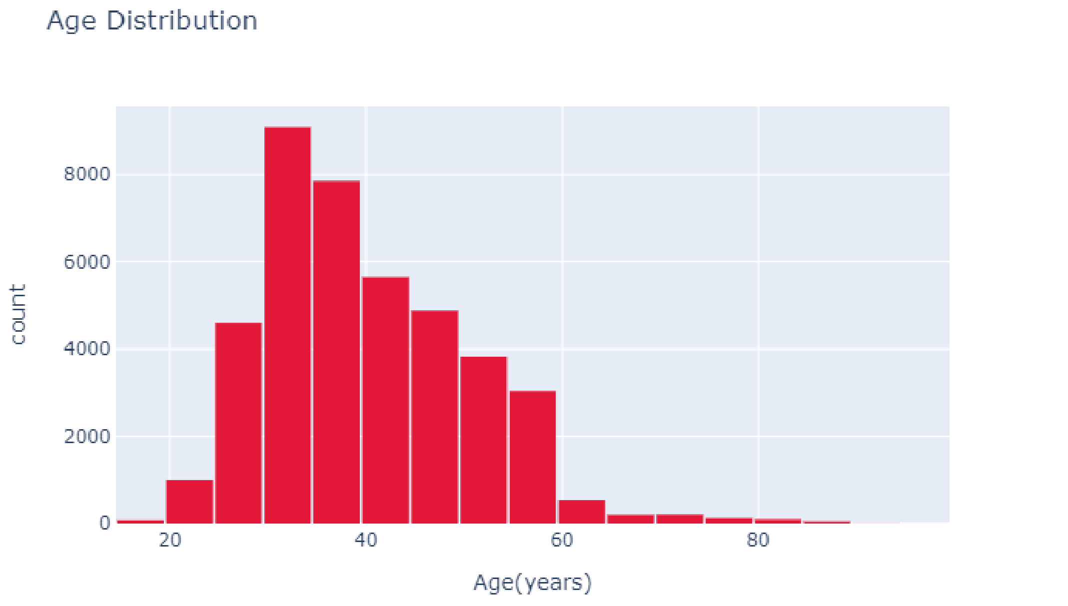
Missing Values	0

Univariant Preliminary Visualization

Numeric Variables

Preliminary Visualization: Numeric Variables

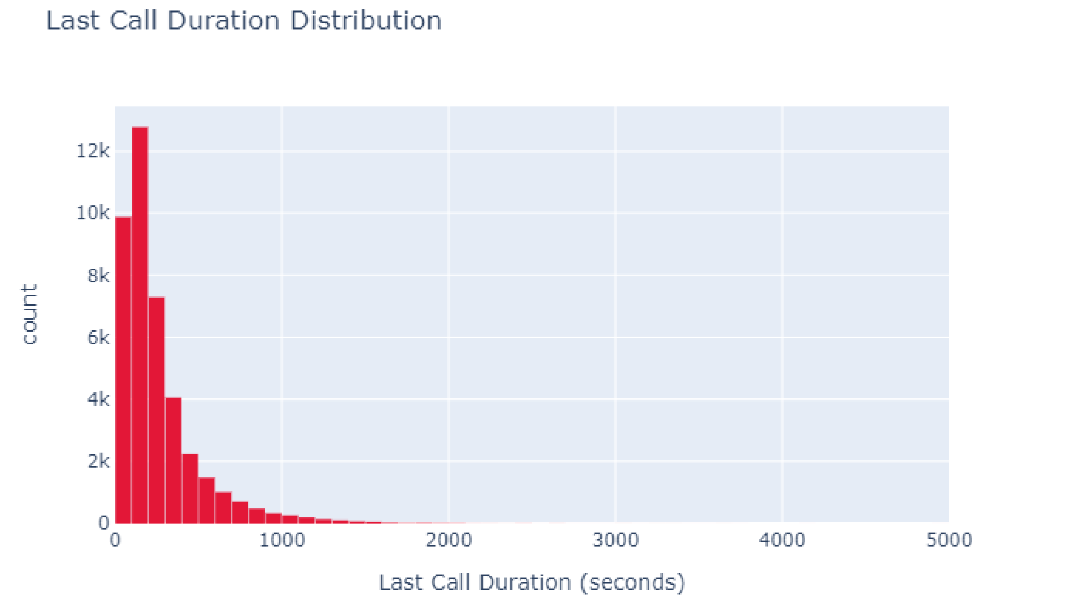
Age



The data for age variable is between 15 and 98 and more than 50% of the clients are younger than 40 years old.

Mean	Median	Var	Distinct No	Skew
40.02	38	108.6	78	Right

LastCall_Dur

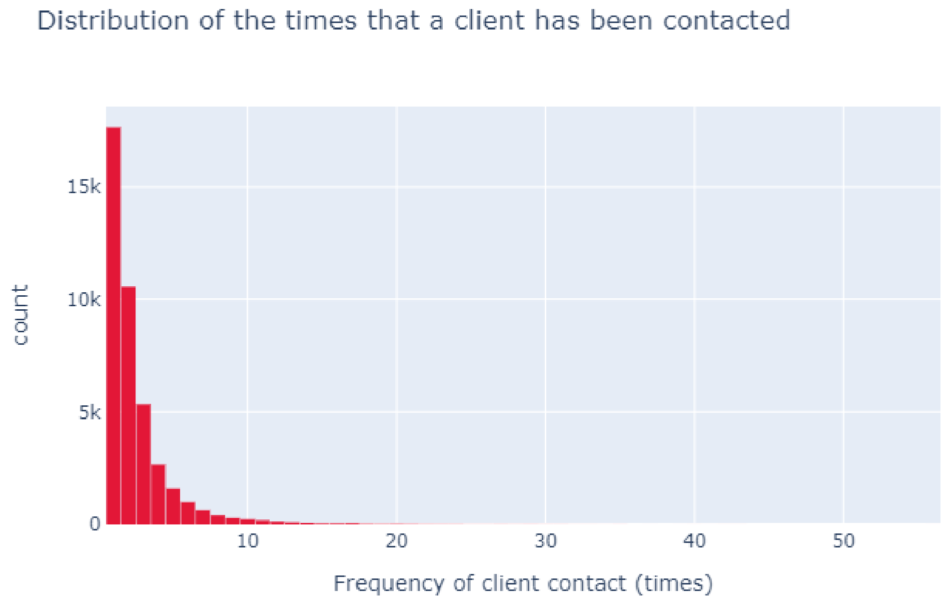


More than 30% of the call durations fall between 100 and 200 seconds. There maybe some outlier data in this variable.

Mean	Median	Var	Distinct No	Skew
258.3	180	259.3	1544	Right

Preliminary Visualization: Numeric Variables

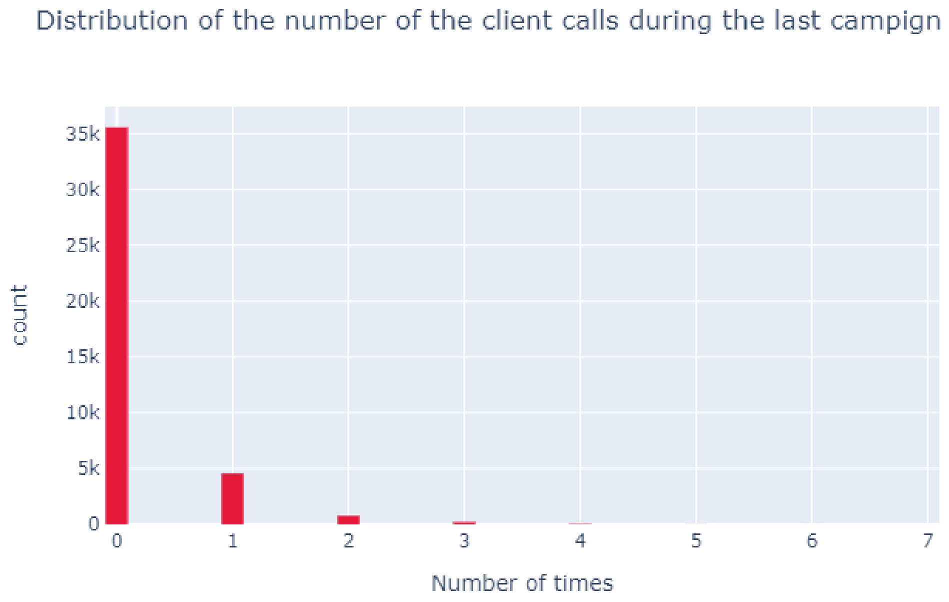
NewCampaign_CallNo



This variable is highly skewed and almost 70% of the observations were under 2. It has a long tail, and it has possible a few outlier data.

Mean	Median	Var	Distinct No	Skew
2.56	2	7.67	42	Right

PrevCampaign_CallNo

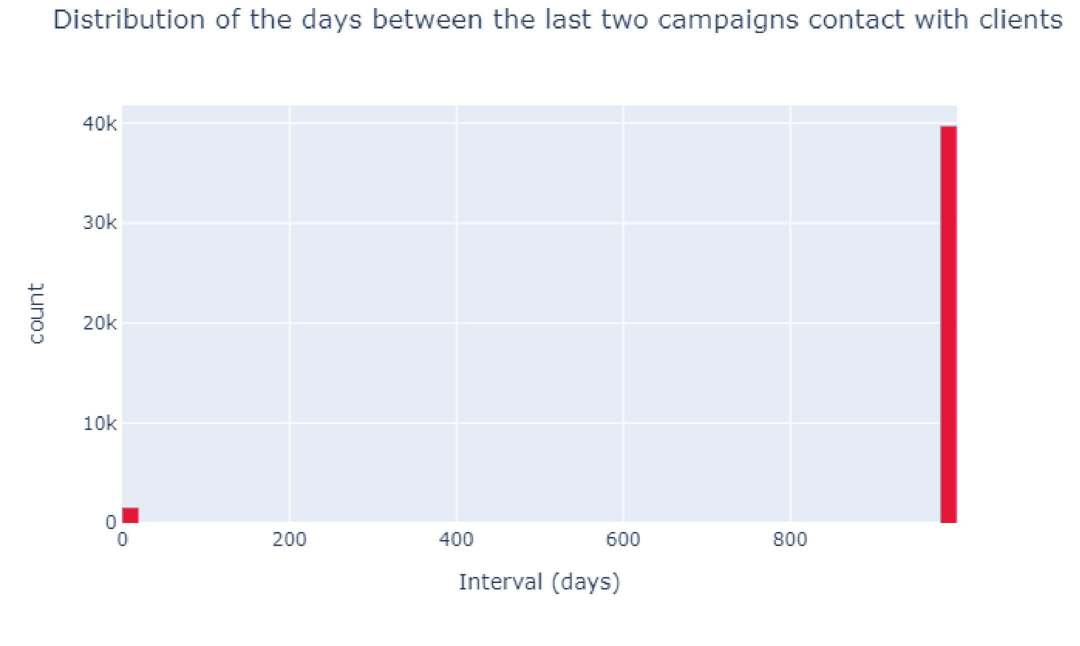


This plot shows that most of the clients has not been included in the previous campaign (about 85%).

Mean	Median	Var	Distinct No	Skew
0.17	0	0.25	8	Right

Preliminary Visualization: Numeric Variables

Campaign_Intervals_Day



This plot is consistent with the previous plot and shows that most of the clients have not been contacted during the previous campaign.

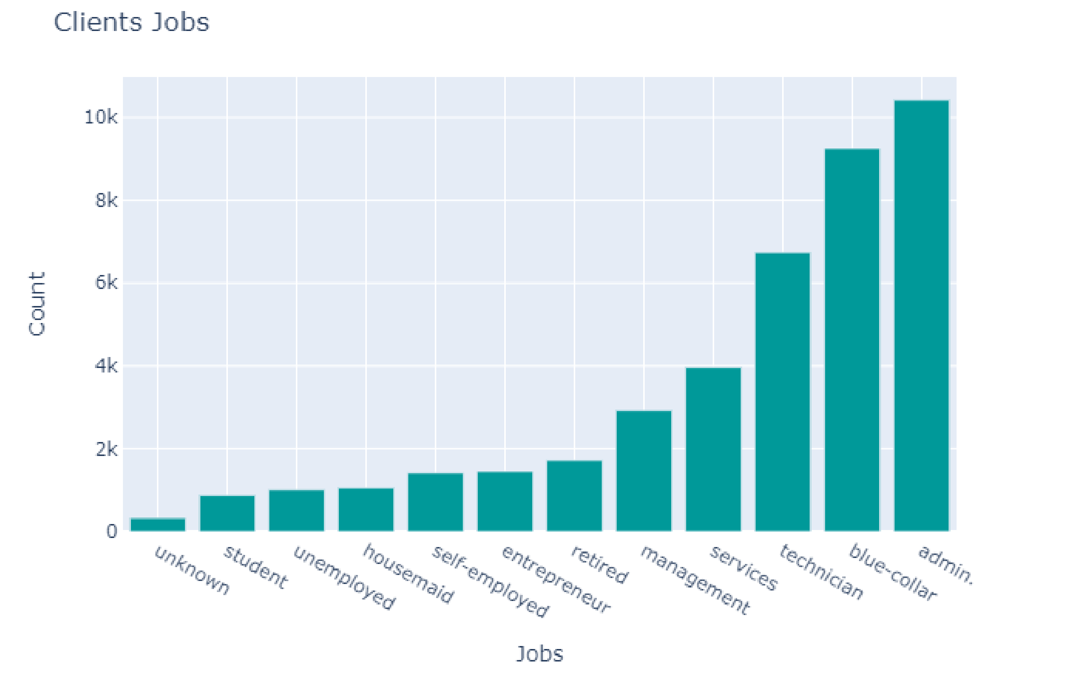
Mean	Median	Var	Distinct No	Skew
962.4	999	186.911	27	Left

Univariate Preliminary Visualization

Categorical Variables

Preliminary Visualization: Categorical Variables

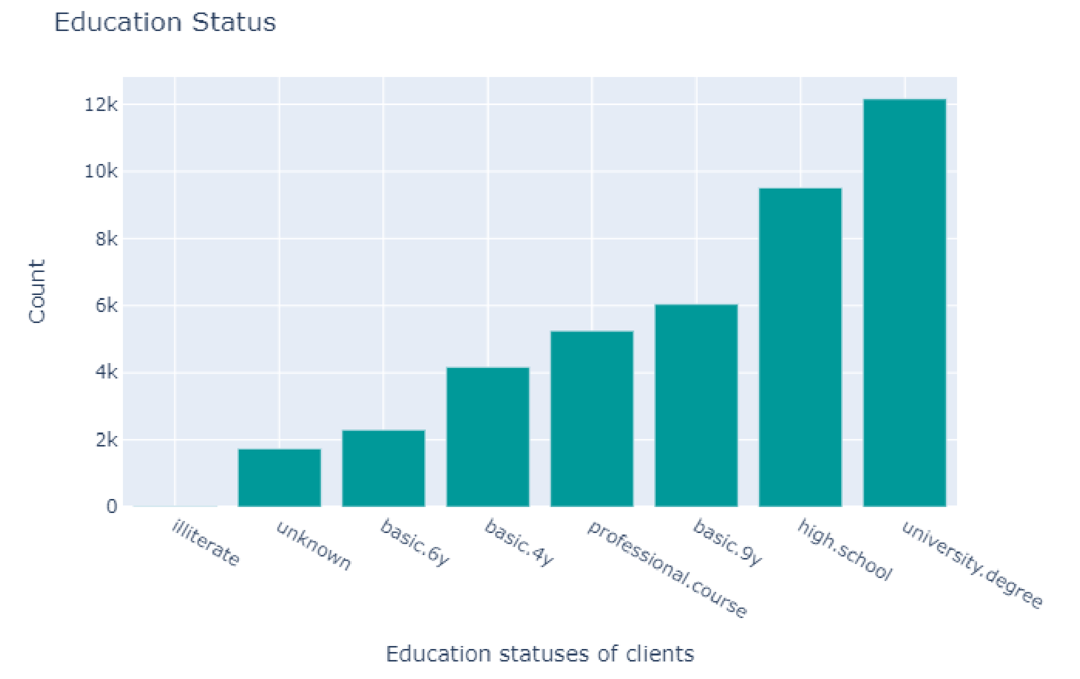
Job



About half of the phone calls are made with clients that either have administrative roles or are blue-collar workers.

Distinct No
12

Education

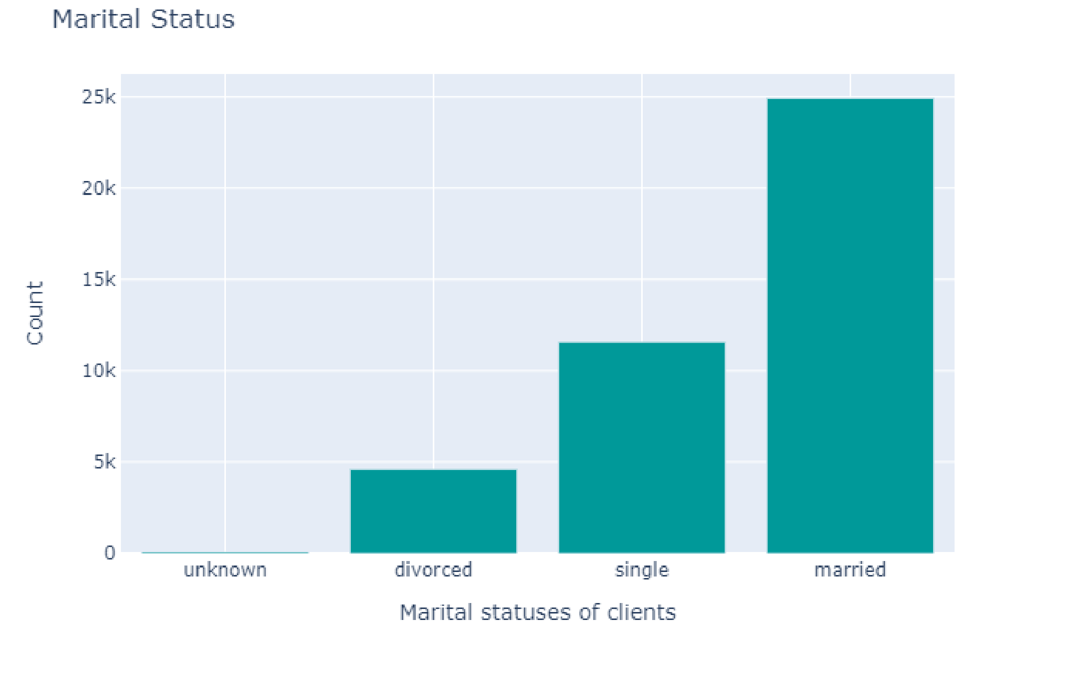


About 50% of the clients in this campaign have at least high-school level education. Education level of about 4% is unknown.

Distinct No
8

Preliminary Visualization: Categorical Variables

Marital



About 60% of the correspondents are married. Comparison of this data with the age group may have interesting outcomes.

Distinct No
4

Credit

Only 3 correspondents have default credits. The status of about 20% of the clients is unknown.

Distinct No
3

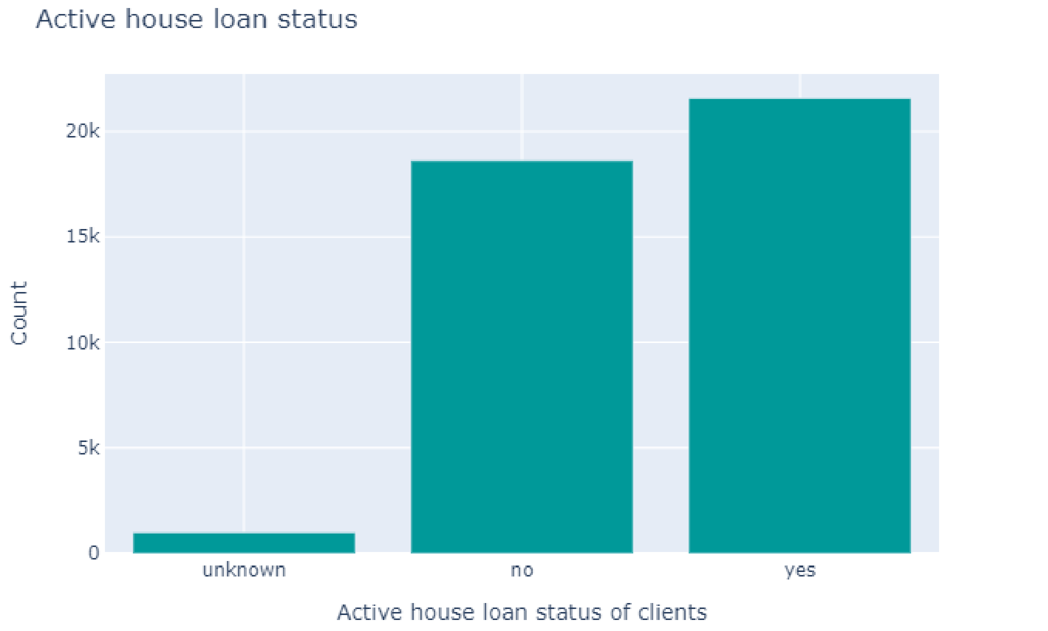
Preliminary Visualization: Categorical Variables

Personal_loan

More than 80% percent of the correspondents have no personal loans.

Distinct No
3

Housing_loan

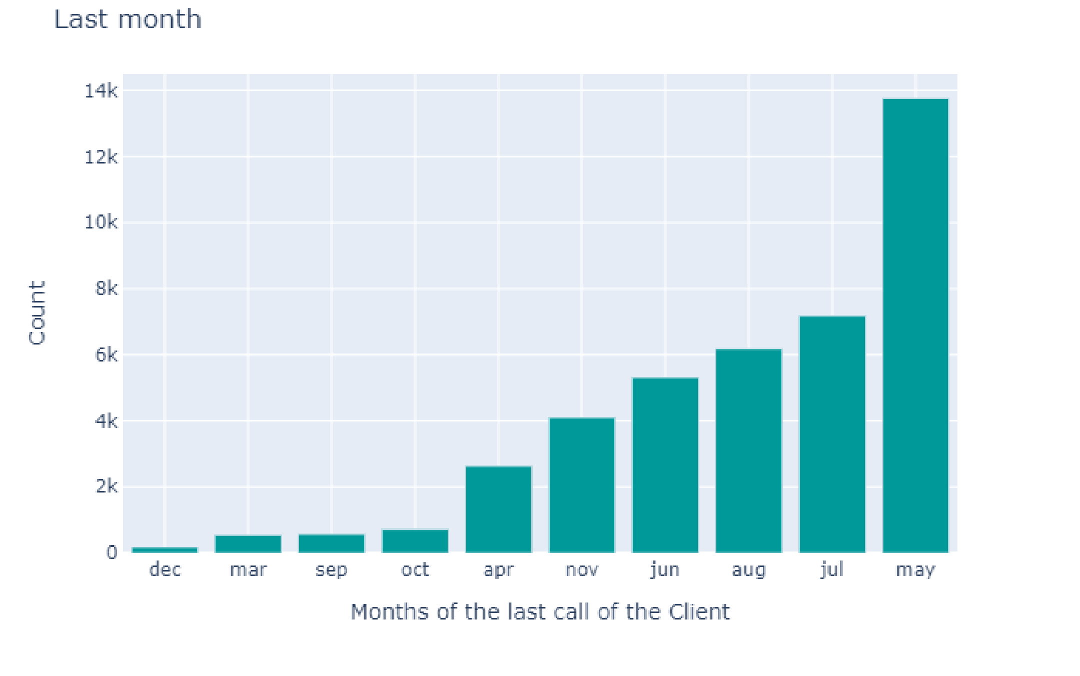


More than 50% of the correspondents have some kind of housing loans.

Distinct No
3

Preliminary Visualization: Categorical Variables

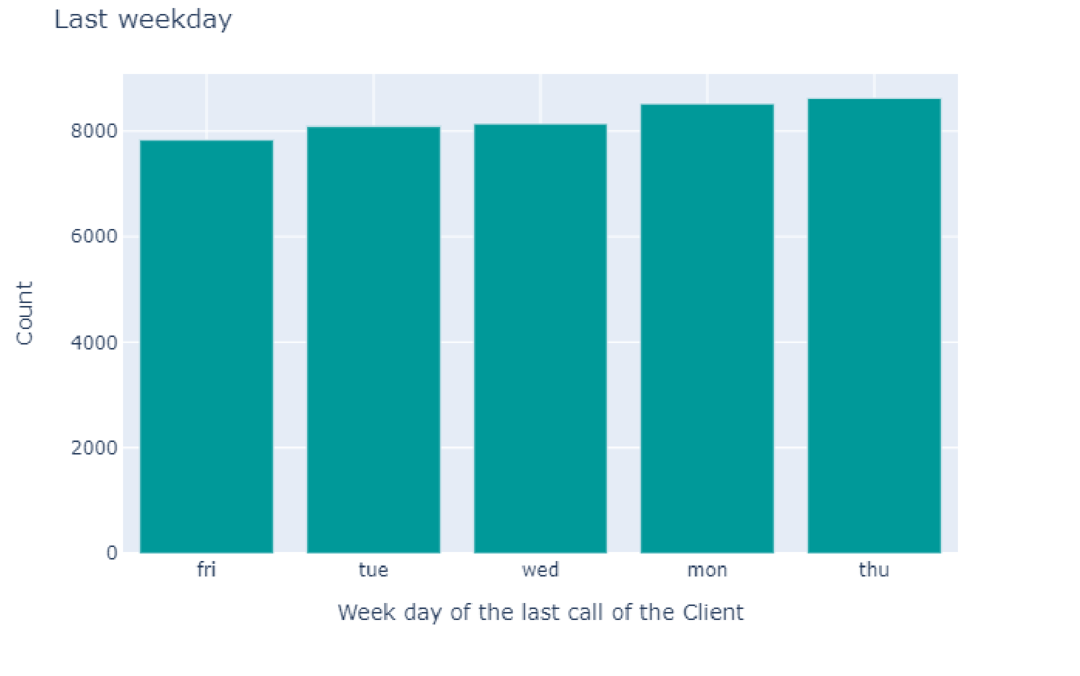
Last_month



No calls were made during January and February. Most of the calls were made during May (approx. 34%).

Distinct No
10

Last_weekday

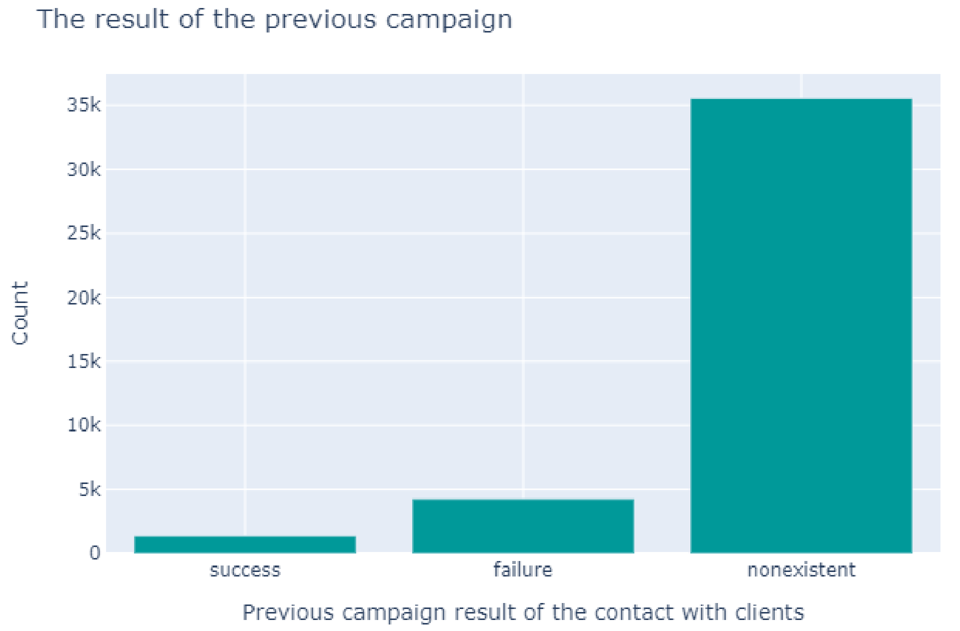


It seems that the calls were made in balance regarding the day of the week that calls were made.

Distinct No
5

Preliminary Visualization: Categorical Variables

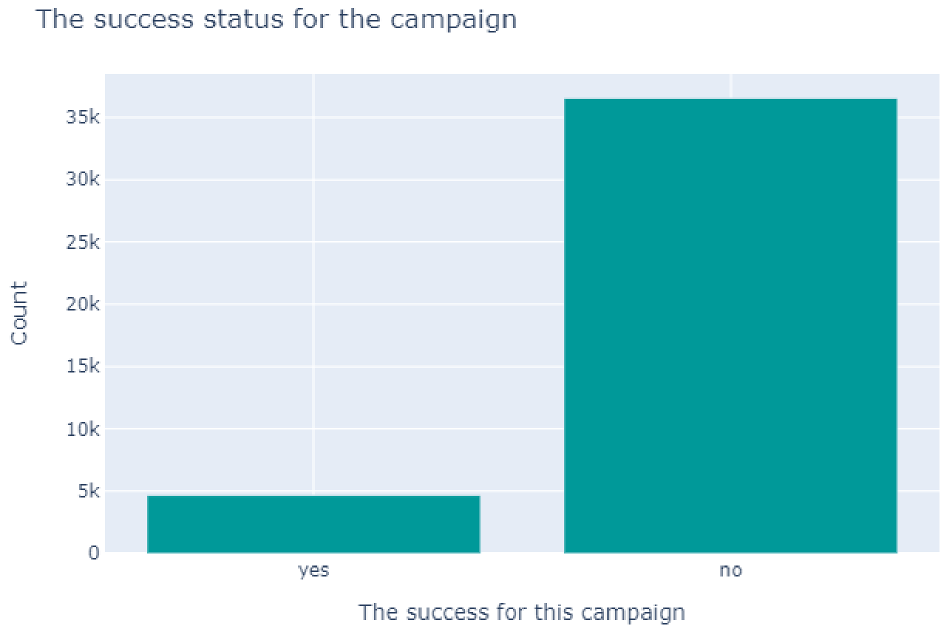
PrevCampaign_Result



It seems majority of the correspondents are selected from clients that have not been targeted during previous campaigns (87%).

Distinct No
3

Campaign_Success

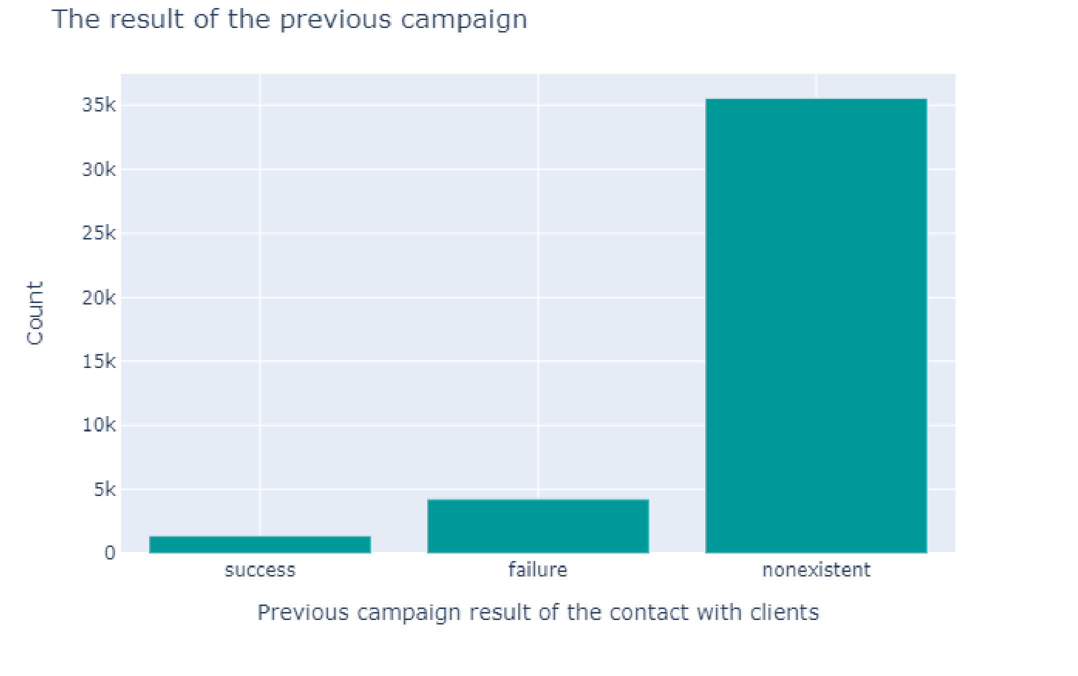


The rate of success (signing up to deposit into a special account) in this campaign was 11.2%

Distinct No
2

Preliminary Visualization: Categorical Variables

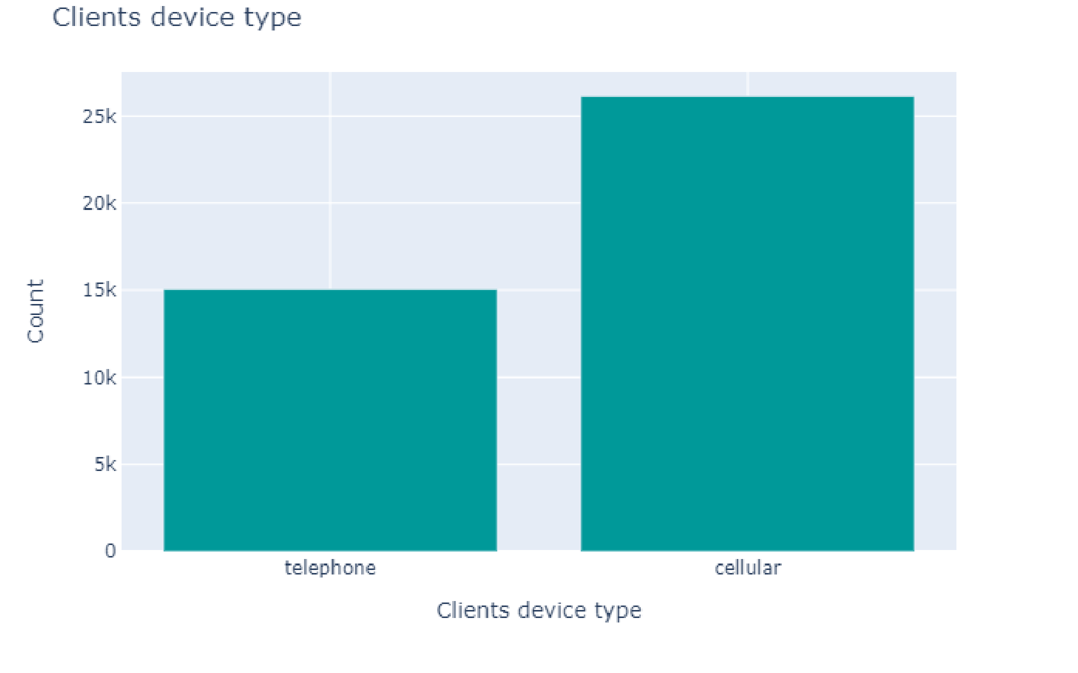
PrevCampaign_Result



It seems majority of the correspondents are selected from clients that have not been targeted during previous campaigns (87%).

Distinct No
3

Call_type

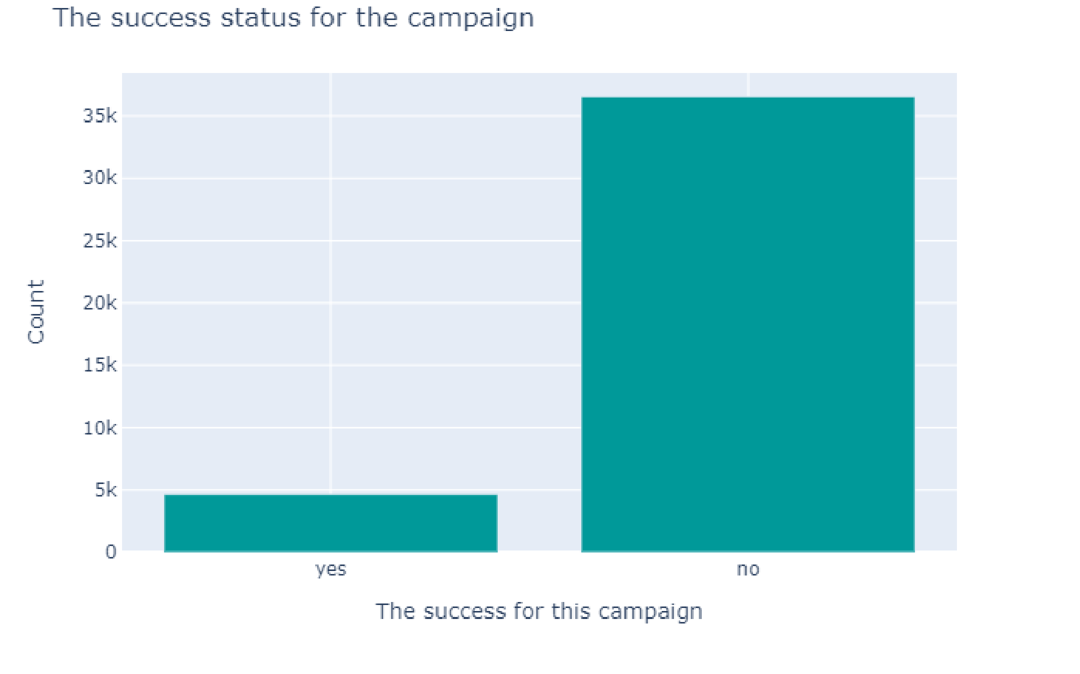


Most of the correspondents were contacted via their cellphones rather than their telephones (63.5% vs. 36.5%).

Distinct No
2

Preliminary Visualization: Categorical Variables

Campaign_Success



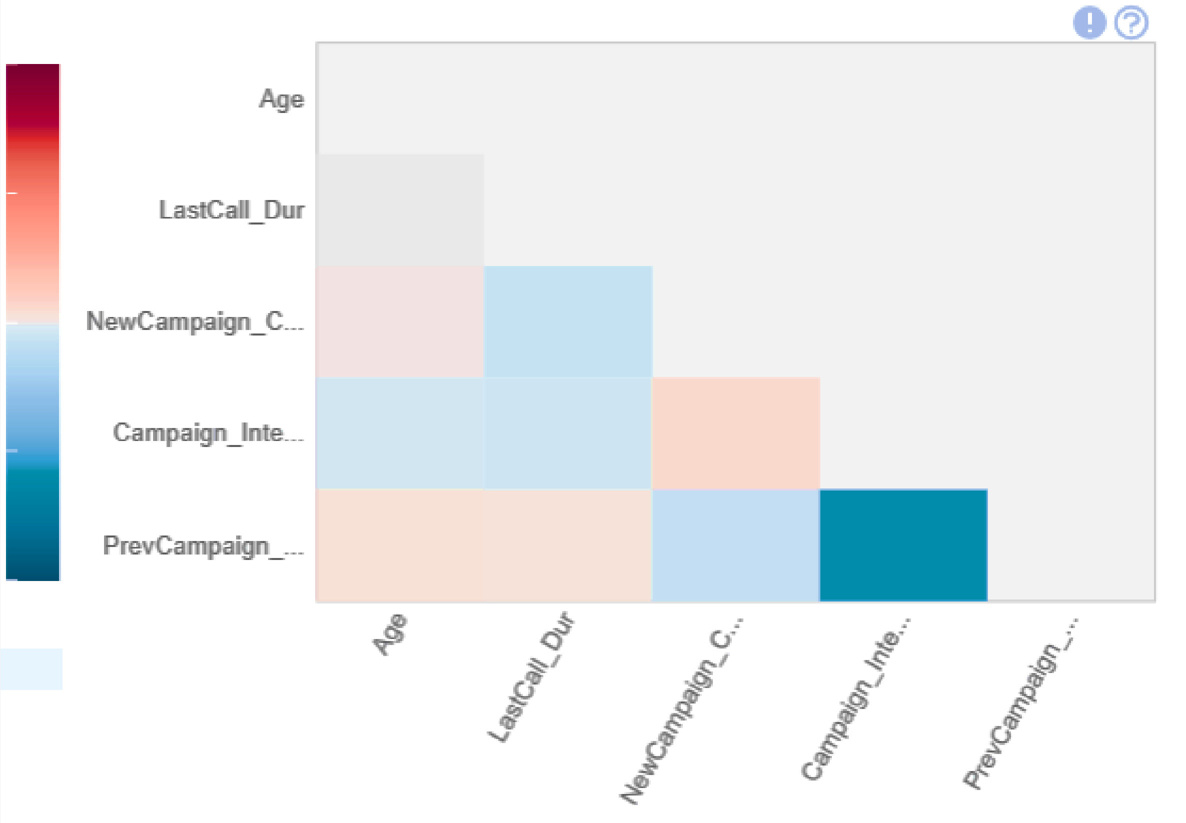
The rate of success (signing up to deposit into a special account) in this campaign was 11.2%

Distinct No
2

Correlations

- Pearson correlation matrix

Pearson correlation matrix (by dataprep.eda)



Cor. Method	Pearson	Spearman	KendallTau
Highest Positive Correlation	0.053	0.056	0.05
Highest Negative Correlation	-0.588	-0.51	-0.5
Lowest Correlation	0.001	0.001	0.001
Mean Correlation	-0.058	-0.054	-0.05

In a general view of the correlation matrix of a subset of the dataset (only the numerical variables are included in this subset), it seems only “PrevCampaign_CallNo” and “Campaign_Intervals_Day” have a considerable negative correlation. This correlation is somewhat expected due to the nature of these variables. More thorough analysis is needed to determine other possible correlations.

Code & Repository Address

- The link of Codes provided in this phase

Code repository Link

The project code could be find in GitHub code repository:

- **Path**: Frz2005> DAB103 > main branch > P1v1.py
- **link**: https://github.com/frz2005/DAB103

Future Exploration & Transformation steps

Future Exploration & Transformation steps

Based on the initial exploration done in this phase these future analysis should be done in this project:

- Determination of outlier data
- Cleaning the data set
- Normalizing variables using appropriate methods
- Additional exploration of correlations
  - Exploring pair correlations
  - Including categorical variables in correlations

Resources

- https://www.investopedia.com/terms/t/telemarketing.asp#:~:text=Key%20Takeaways-,Telemarketing%20is%20the%20direct%20marketing%20of%20goods%20or%20services%20to,lead%20generation%2C%20and%20sales%20calls
- https://data.world/data-society/bank-marketing-data
- https://qlutch.com/telemarketing/create-a-plan-for-a-telemarketing-campaign
- https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

THANK YOU