Banking Marketing

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Goal, Metric, and Objective

Goal

Increase conversion rate up to 14%

Metric

Conversion Rate

Objective

- Analyze factors that cause low conversion rate
- Predict customer will convert or not

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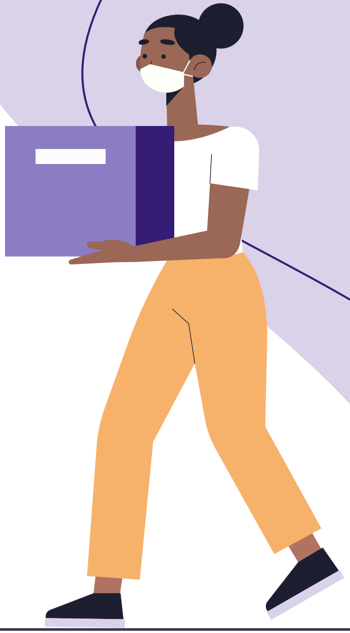
Project Background

Background, Metric, Objective and Goals

02

Exploratory Data Analysis

Data Exploration & Business Insights



Dataset Overview

1 Year Historical Data (41.188 Clients & 20 Features)

Bank Client Data

- Age
- Job
- Marital Status
- Education
- Default
- Housing
- Loan

Related to Last Contact

- Contact
- Month
- Day of Week
- Duration

Social & Economic Attribute

- Emp.Var.Rate
- Cons.Price.Idx
- Cons.Conf.Idx
- Euribor3m
- Nr.Employed

*) Detail Features Dictionary Written On Appendix

Dataset Overview

1 Year Historical Data (41.188 Clients & 20 Features)

Other Atributes

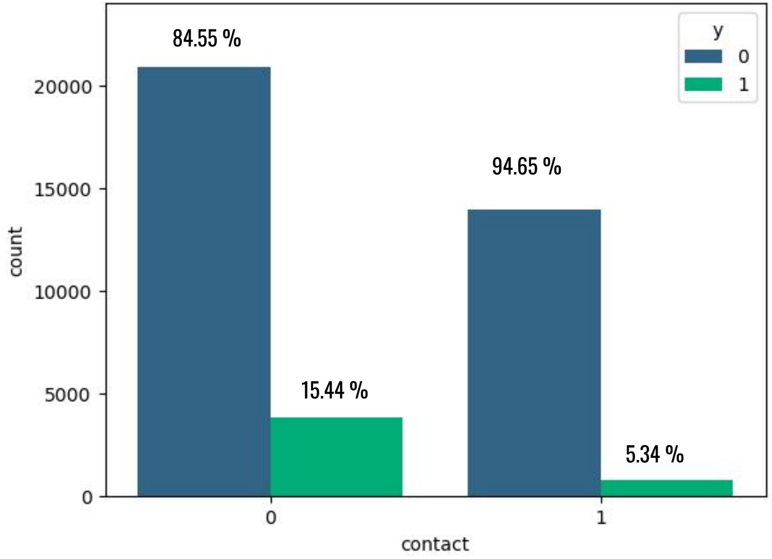
- Campaigns
- Pdays
- Previous
- Poutcomes

Y - Target Feature

Has the client subscribed a term deposit?

*) Complete Features Dictionary Written On Appendix

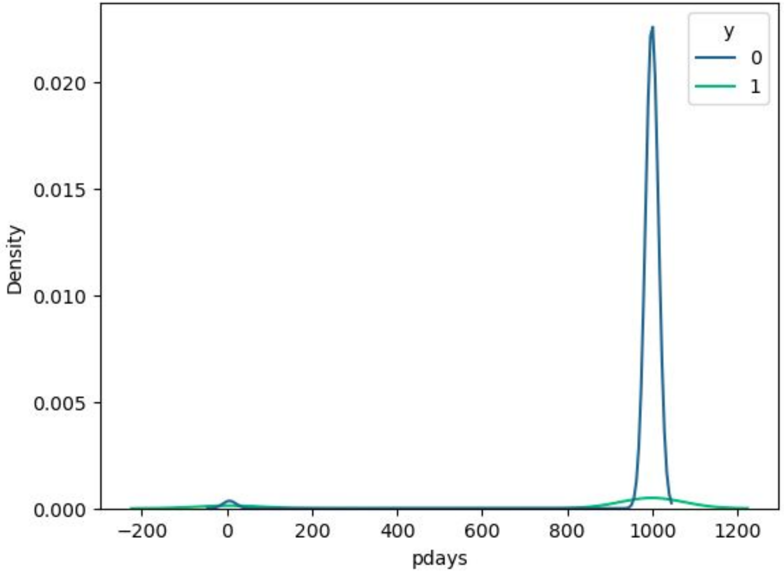
Data Exploration - Contact



Cellular users have slightly higher customers who subscribe term of deposit. It has also higher probability to subscribe (**15.44 %**)

*) contact → contact communication type. Cellular = 0, Telephone = 1

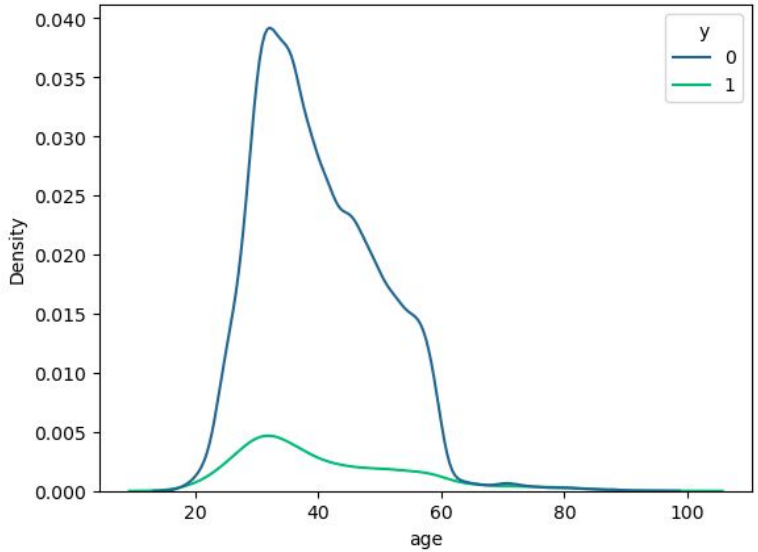
Data Exploration - Pdays



This feature has **high number of clients who was not previously contacted**. We will explore how this features affect target feature

*) **Pdays**: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

Data Exploration - Age



Our clients contains of people around 20-60 years old, but majority of them are in **30-40 years old.** In the next exploration, we will find how age affect to our target feature.

*) Age : How old our client is

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Data Preprocessing

Data Pre Processing

1. Drop Duplicate Values

1784 values dropped.
Data is clean, no need to handling missing values

2. Feature Engineering

Engineered features:
Education, Default, Contact, Target Feature

3. Feature Encoding

Using One Hot Encoder:
As a result, there are 40 additional encoded features

4. Outlier Detection

No extreme/weird values found, no need to do outlier handling

Data Pre Processing

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Feature Scaling

Using MinMaxScaler to scale X_train and X_test

6

Feature Selection

Using filter method: chi square, mutual info, quasi, univariate feature selection

7

Handling Target Imbalanced

Using SMOTE with default sampling strategy (1:1)

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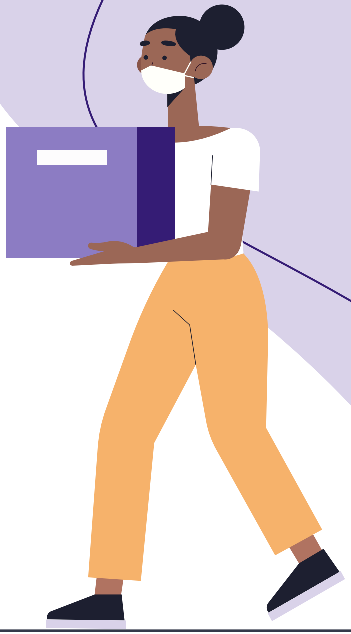
Modeling

Basic Model, Hyperparameter Tuning, Feature Importance



Classification Model

	Model	Accuracy	Precision	Recall	F2-Score
0	XGBClassifier	0.89	0.51	0.36	0.38
1	AdaBoostClassifier	0.84	0.37	0.59	0.53
2	RandomForestClassifier	0.87	0.44	0.40	0.41
3	LogisticRegression	0.77	0.29	0.66	0.52
4	DecisionTreeClassifier	0.87	0.43	0.34	0.36
5	KNeighborsClassifier	0.87	0.43	0.47	0.47

Focus on Recall Score to minimize False Negative (Predicted **will not subscribe** term of deposit, but **actually subscribe**). We consider marketing cost that give customers who predicted as not subscribe is costly. Then, we will do hyperparameter tuning on:

- AdaBoost Classifier
- Random Forest
- Logistic Regression
- KNeighbors

Because they have high F2 Score

Hyperparameter Tuning

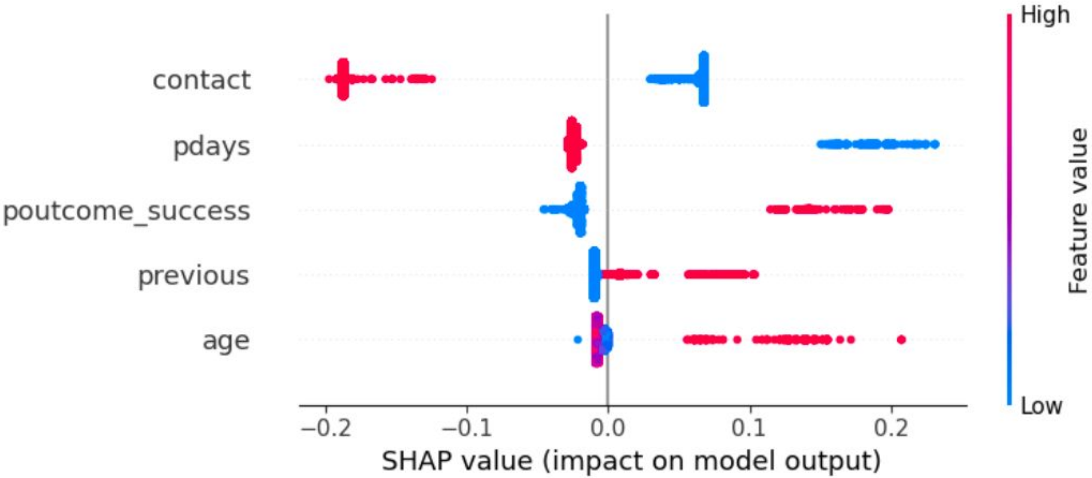
	Train Recall Score	Test Recall Score
Logistic Regression	0.83	0.83
Random Forest	**0.85**	**0.83**
Ada Boost	0.85	0.83
Kneighbors	0.59	0.59

We did 2x hyperparameter tuning, 1st aim to filter good predictive features. As a result we found top 5 predictive features, then 2nd hyperparameter focus on finding good recall score. Top 2 model are:

- AdaBoost Classifier
- Random Forest

Then we decided to choose **Random Forest** because it has **better importance features interpretation** rather than Adaboost.

Feature Importances



We can see that:

- Customer who contacted using cellular tend to be more subscribe to term of deposit
- Customers who are frequently contacted (recently contacted) tend to be more subscribe to term of deposit
- etc

*) contact → Cellular = 0, Telephone = 1
*) pdays → number of days that passed by after the client was last contacted from a previous campaign
*) poutcome_succes → outcome of the previous marketing campaign
*) previous → number of contacts performed before this campaign and for this client

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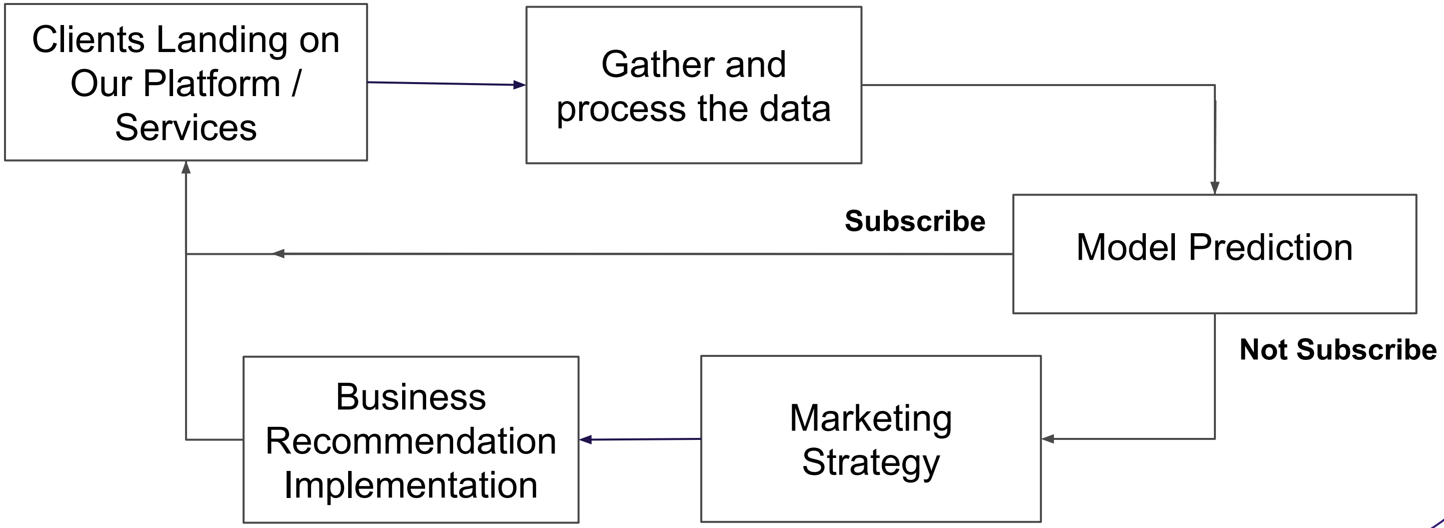
Business Insights and Recommendation

Business Simulation, Insights, and Recommendation

How Our Model Works?



Business Insights & Recommendation

Based On SHAP Values Feature Importance

Contact	Pdays	Poutcome Success	Previous	Age
For re-marketing purpose, **only target cellular users** to get more probability of subscribed term of deposit	**Keep inform / offer and contact our clients** to clients regularly using recommended platform (cellular)	To get more clients, For re-marketing purpose, **only target clients who previously accept our campaign**.	The **more contact performed** / make offers increase the client's probability to subscribe our product	**The older clients tend to be more subscribe term of deposit** rather than the younger one. For remarketing purpose, only target the older generation

*) For the next step, we will try to implement recommendation above using simulation

Business Simulation

Before

Without modeling, the Bank run blind marketing campaign and random strategy

Current Conversion Rate :
11.67 % / Year

After

With prediction model, the Bank run targeted campaign and segmented marketing strategy[1]

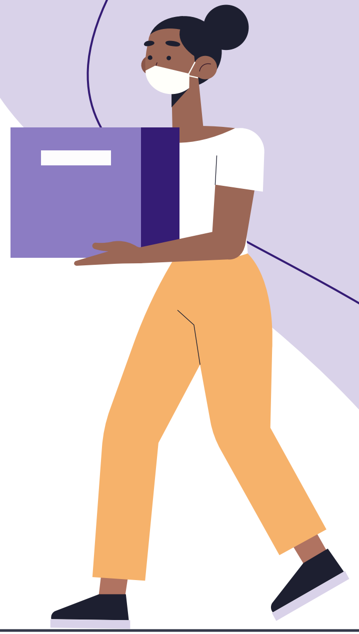
New Conversion Rate :
14.73 % / Year

After implementing the strategy, the bank can increase Conversion Rate up to **3.06%**

*) Strategy : target only cellular users, who had contacted recently, and they are around 30-50 years old

Thank You

Appendix



Features Dictionary

Bank Client Data

1. **Age** (numeric)

2. **Job** : type of job
   (categorical:'admin.', 'blue-collar', 'entrepreneur', 'housemaid', 'management', 'retired', 'self-employed', 'services', 'student', 'technician', 'unemployed', 'unknown')

3. **Marital** : marital status
   (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)

4. **Education**
   (categorical: 'basic.4y', 'basic.6y', 'basic.9y', 'high.school', 'illiterate', 'professional.course', 'university.degree', 'unknown')

5. **Default**: has credit in default? (categorical: 'no','yes','unknown')

6. **Housing**: has housing loan? (categorical: 'no','yes','unknown')

7. **Loan**: has personal loan? (categorical: 'no','yes','unknown')

Features Dictionary

Related With the Last Contact of the Current Campaign:

8. **Contact**: contact communication type (categorical: 'cellular','telephone')
9. **Month**: last contact month of year (categorical: 'jan', 'feb', 'mar', …, 'nov', 'dec')
10. **Day of week**: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

Other Attributes

11. **Campaign**: number of contacts performed during this campaign and for this client (numeric, includes last contact)
12. **Pdays**: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
13. **Previous**: number of contacts performed before this campaign and for this client (numeric)
14. **Poutcome**: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

Features Dictionary

Social and Economic Context Attributes:

8. **Emp.var.rate**: employment variation rate - quarterly indicator (numeric)
9. **Cons.price.idx**: consumer price index - monthly indicator (numeric)
10. **Cons.conf.idx**: consumer confidence index - monthly indicator (numeric)
11. **Euribor3m**: euribor 3 month rate - daily indicator (numeric)
12. **Nr.employed**: number of employees - quarterly indicator (numeric)

Target Feature

13. **Y** - has the client subscribed a term deposit? (binary: 'yes','no')