

# Final Report

Week 13 - LISUM 04
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18/12/21

# Agenda

**Business Problem Background** 

**Brief EDA** 

Models

Models' Metrics

**Chosen Model** 

Deployment

**Final Conclusions** 



# Business Problem Background

#### **Problem Description**

ABC bank is about to launch its new product, a term deposit. Before the launching, they want to develop a model which help them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with bank or other Financial Institution).

#### Why?

To shortlist customer whose chances of buying the product is more so that their marketing channel (tele marketing, SMS/email marketing etc) can focus only to those customers whose chances of buying the product is more.

#### **Dataset information**

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.

#### Goal

Through a Machine Learning Model, determine if the customer is accepting the term deposit or is not.

#### **Dataset:**

Number of rows: 41188 - Number of columns: 21

#### **Assumptions:**

- "Unknown" will be treated as a category, not as NaN.
- Outliers presented in age and campaign.

#### **Features:**

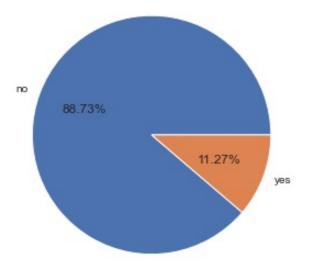
```
['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'],
```

#### **Target distribution:**

```
Distribution of target (%):

y
no 88.734583
yes 11.265417
```

#### **Target distribution:**



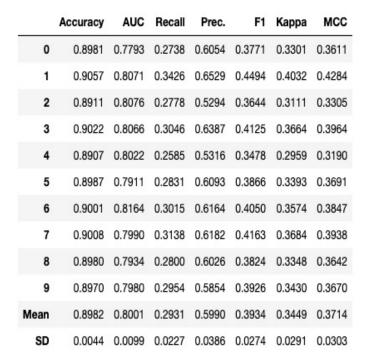




	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lightgbm	Light Gradient Boosting Machine	0.8960	0.8001	0.3245	0.5671	0.4126	0.3602	0.3772	0.6410
catboost	CatBoost Classifier	0.8976	0.7950	0.3104	0.5866	0.4057	0.3555	0.3772	6.8270
Ir	Logistic Regression	0.8239	0.7908	0.6367	0.3468	0.4489	0.3548	0.3781	0.6580









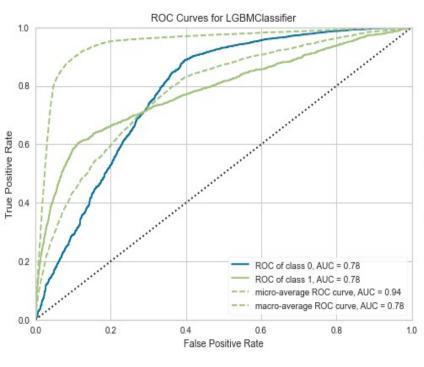
### CatBoost

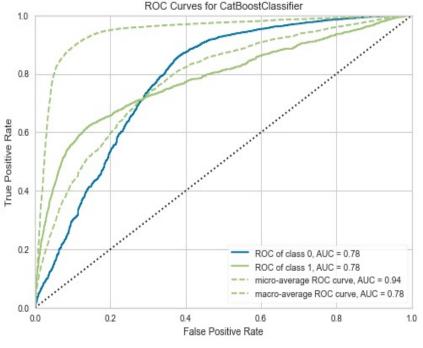
	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.8967	0.7753	0.2892	0.5839	0.3868	0.3374	0.3623
1	0.9022	0.8060	0.3488	0.6141	0.4449	0.3957	0.4148
2	0.8907	0.8095	0.2932	0.5249	0.3762	0.3216	0.3380
3	0.8994	0.8005	0.2831	0.6174	0.3882	0.3415	0.3726
4	0.8956	0.7961	0.2954	0.5714	0.3895	0.3386	0.3608
5	0.8998	0.7925	0.3015	0.6125	0.4041	0.3562	0.3831
6	0.8991	0.8177	0.3231	0.5966	0.4192	0.3692	0.3901
7	0.8963	0.7875	0.3169	0.5722	0.4079	0.3562	0.3749
8	0.8942	0.7837	0.2769	0.5625	0.3711	0.3206	0.3447
9	0.8911	0.7822	0.3046	0.5294	0.3867	0.3317	0.3470
Mean	0.8965	0.7951	0.3033	0.5785	0.3975	0.3469	0.3688
SD	0.0036	0.0127	0.0203	0.0315	0.0210	0.0219	0.0222

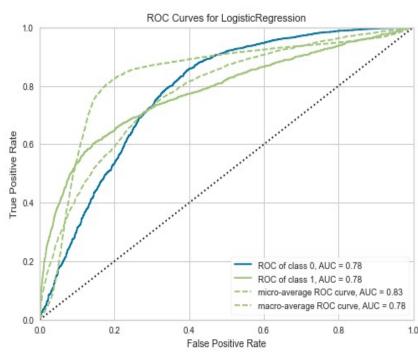
	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.8204	0.7690	0.5877	0.3322	0.4244	0.3276	0.3464
1	0.8189	0.8010	0.6759	0.3443	0.4562	0.3611	0.3907
2	0.8182	0.7908	0.6481	0.3387	0.4449	0.3488	0.3751
3	0.8266	0.8006	0.6154	0.3478	0.4444	0.3510	0.3710
4	0.8345	0.8018	0.6615	0.3694	0.4741	0.3851	0.4082
5	0.8339	0.7881	0.6123	0.3605	0.4538	0.3635	0.3813
6	0.8273	0.8073	0.6738	0.3584	0.4679	0.3761	0.4029
7	0.8193	0.7836	0.6369	0.3393	0.4428	0.3467	0.3712
8	0.8200	0.7758	0.6215	0.3378	0.4377	0.3415	0.3641
9	0.8210	0.7904	0.6338	0.3416	0.4440	0.3485	0.3722
Mean	0.8240	0.7908	0.6367	0.3470	0.4490	0.3550	0.3783
SD	0.0059	0.0116	0.0271	0.0113	0.0138	0.0160	0.0174





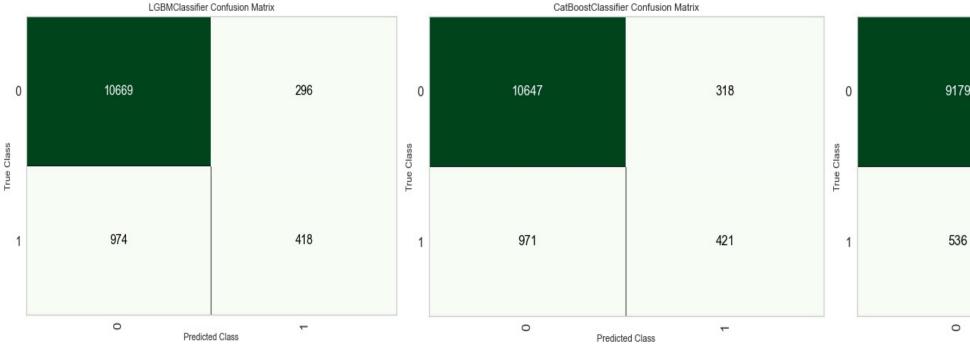


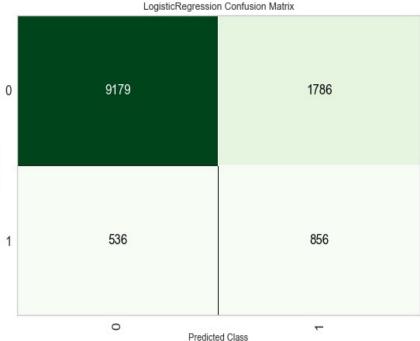








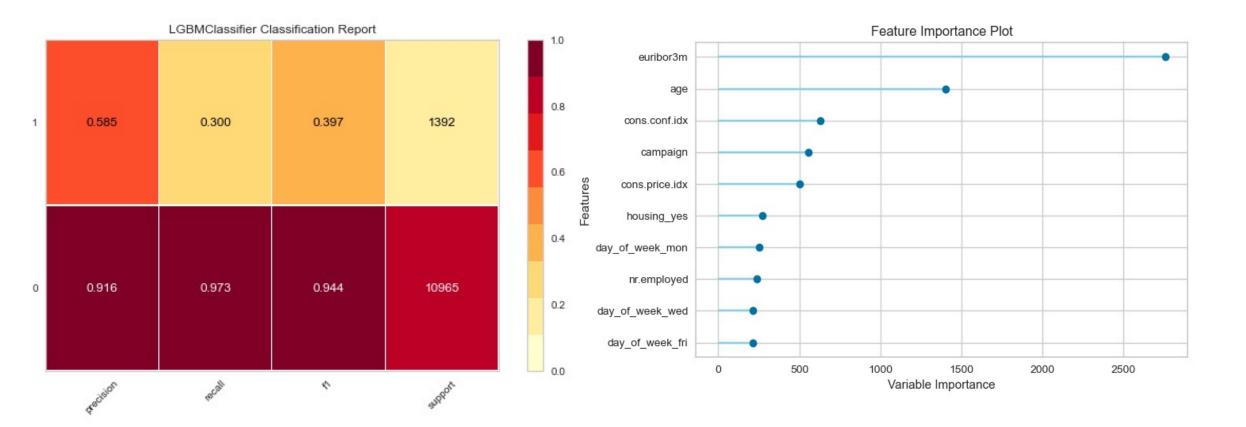






The chosen model was LightGBM. Our criteria for choosing was based on AUC, because is the best indicator for binary problems.

Some additional metrics of our chosen model:





Similar to week 5, the deployment was on Heroku as a simple API that predicts the acceptance of bank customers. As we already know, the Machine Learning Model is Light GBM.



Deposi	t
Purcha	se
Predict	ion
Age	
job	
marital	
education	
housing	
loan	
contact	
month	
day_of_week	
duration	
campaign	
pdays	
previous	
poutcome	
emp.var.rate	
cons.price.idx	
cons.conf.idx	
euribor3m	
nr.employed	

- We tried different treatment for outliers and missing values, but finally the best results came from WOE treatment, and to keep "unknown" as its own category. We experimented considering them as nulls, but the metrics got worse.
- Through Pycaret, we tried several models, but we went deeper in the first three: LightGBM, Catboost and Logistic Regression. After analysis, the model we chose for our model was LightGBM. It arrives to better predictions.
- It would be interesting to analyse Threshold optimization, because some metrics, such as precision and recall are low.



We implemented pycaret library to know the model would perform better in our business problem.

The criterion was based mainly in AUC (area under the curve), the results were:

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lightgbm	Light Gradient Boosting Machine	0.8960	0.8001	0.3245	0.5671	0.4126	0.3602	0.3772	0.6410
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We are going to try with the 2 best models:

- 1) Light Gradient Boosting Machine
- 2) CatBoost Classifier

Next week we are going to implement some Grid Search and hyperparameters optimization to get the ideal model.

## Thank You

