Parcours Data Scientist

Projet N°7 : Implémentez un modèle de scoring

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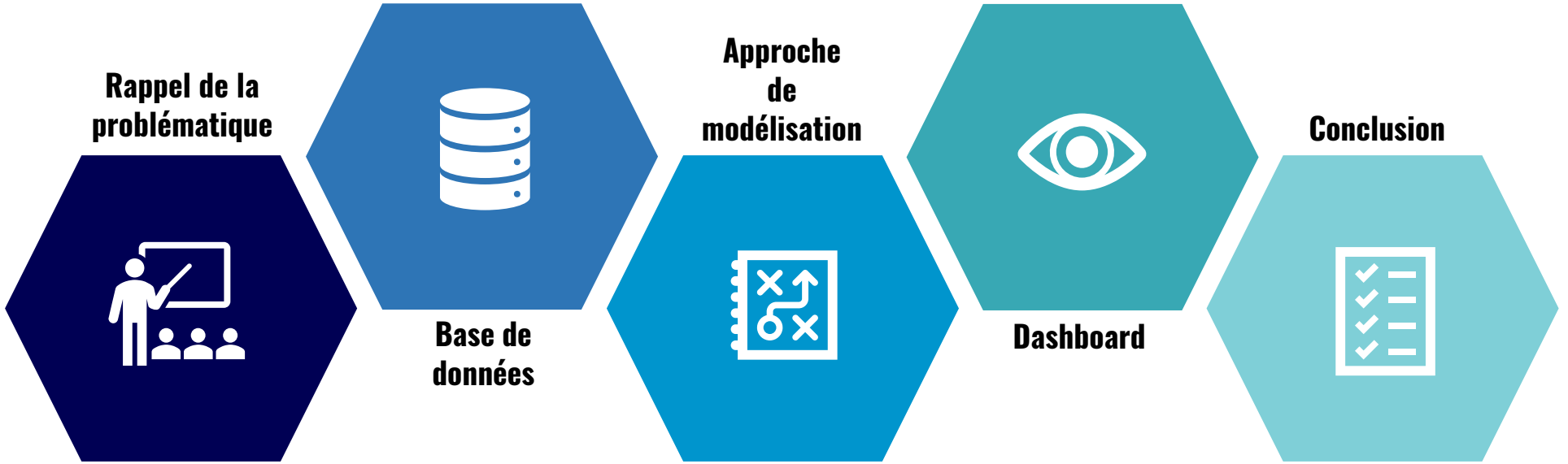
Sommaire


Rappel de la problématique
Base de données
Approche de modélisation
Dashboard
Conclusion

Rappel de la problématique

Data Scientist au sein de la société "**Prêt à dépenser**", qui propose des crédits à la consommation pour des personnes ayant peu ou pas du tout d'historique de prêt.

1. Mettre en œuvre un outil de « scoring crédit »
2. Classifier la demande en crédit accordé ou refusé

à partir de :

→ **données comportementales**
→ **données provenant d'autres institutions financières,**
→ **etc**

L'intention de ce projet est de réaliser un projet de bout en bout jusqu'à sa mise en production.

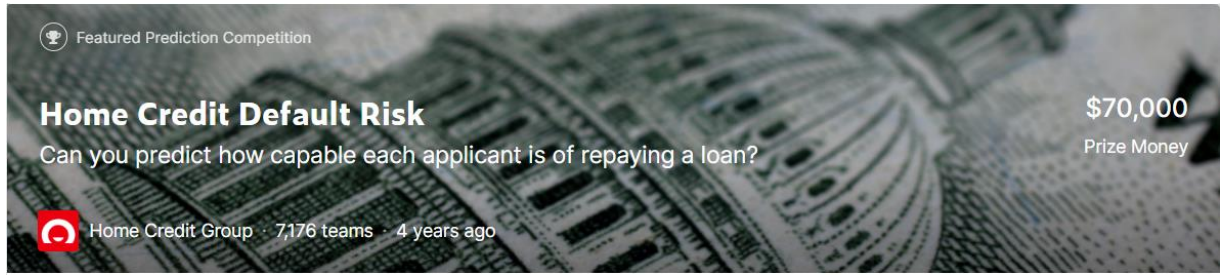
Points importants :

→ Transparence de la décision de crédit
→ Dashboard interactif avec informations personnelles du client

Partie I – Base de données et Analyse

Image : facilogi.com

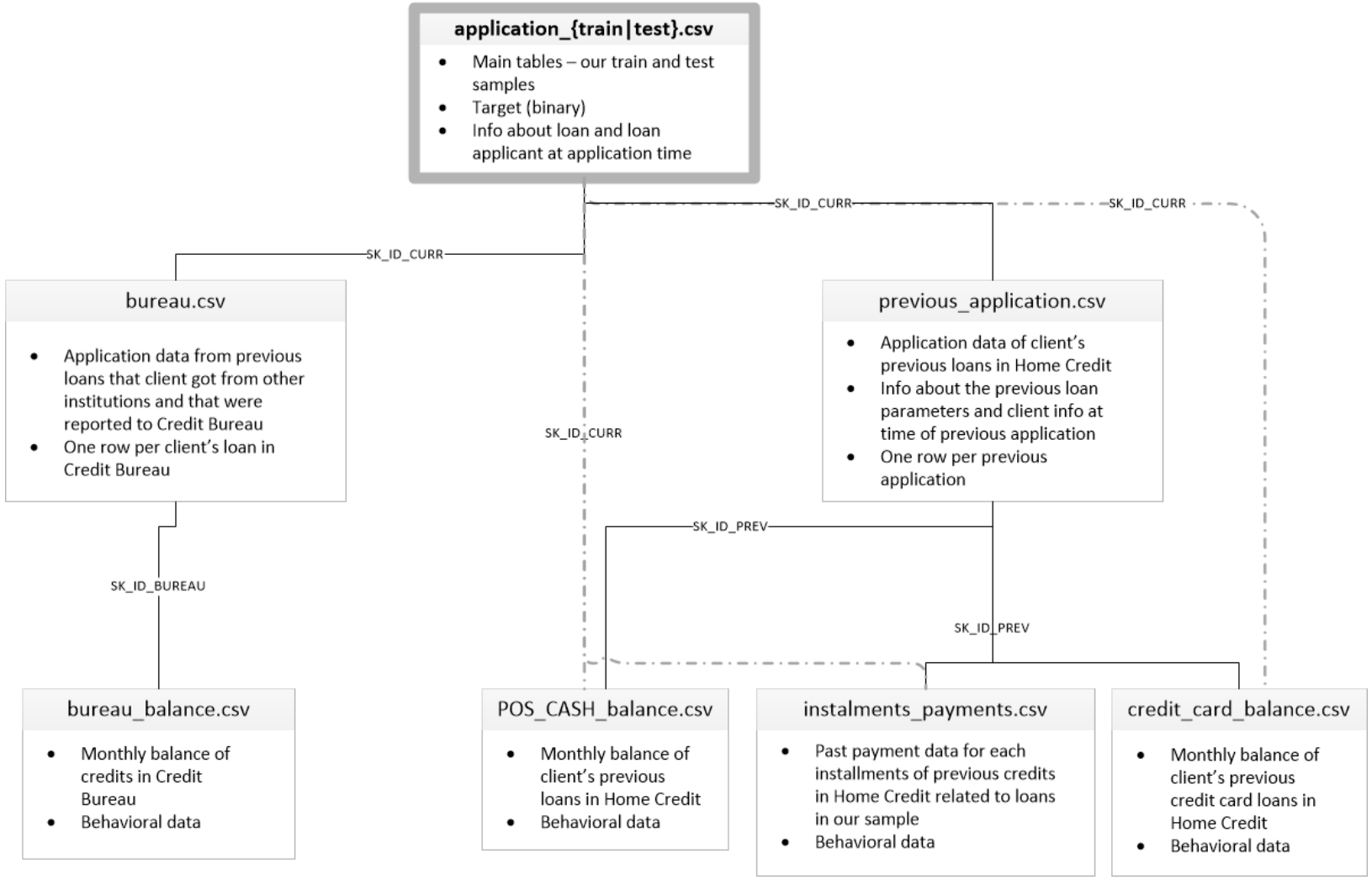
I – Les données



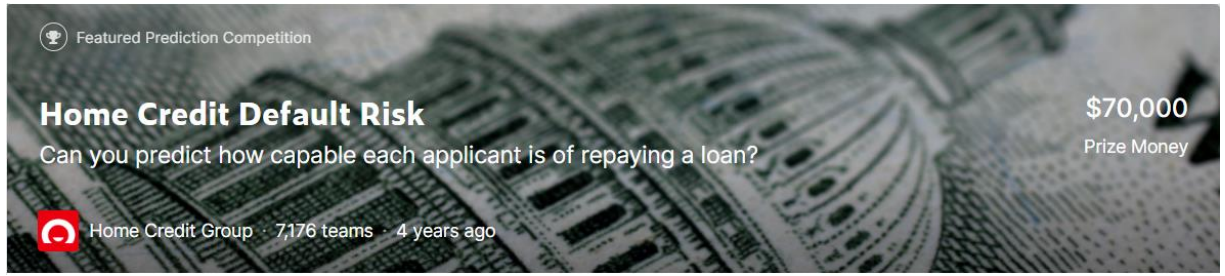
Home Credit Default Risk

7 bases de données

- application_train/test
- bureau
- bureau_balance
- Previous application
- POS_CASH_balance
- Instalments_payments
- credit_card_balance



I – Les données



Home Credit Default Risk

Focus sur application_train
+ (HomeCredit_columns_descriptions)

Information personnelles :
- Profession,
- Famille,
- Possessions immobilières
- etc

application_{train|test}.csv

- Main tables – our train and test samples
- Target (binary)
- Info about loan and loan applicant at application time

	attributs	valeurs_manquantes	type	Com
76	COMMONAREA_MEDI	69.872297	float64	Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor
48	COMMONAREA_AVG	69.872297	float64	Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor
62	COMMONAREA_MODE	69.872297	float64	Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor
70	NONLIVINGAPARTMENTS_MODE	69.432963	float64	Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor
56	NONLIVINGAPARTMENTS_AVG	69.432963	float64	Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

I – Analyse de donnée

Restriction à la base de donnée application_train.csv
(307511, 122)

Unbalanced values (+ de 90% de la classe 0)

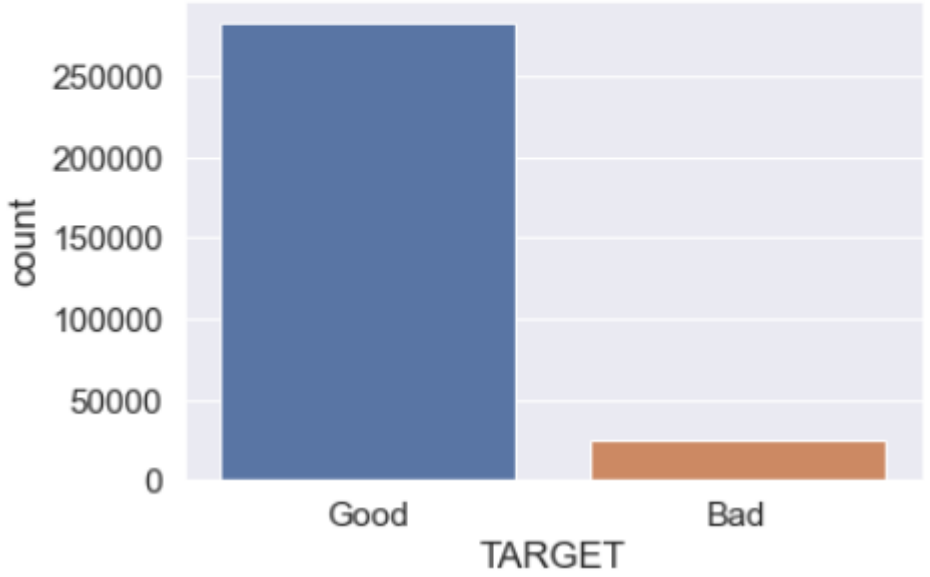
Analyse du jeu de données
(Inspiré du kaggle de Will Koehrsen)

Feature engeniering

Missing values (itérative Imputer)

Train / Test dataframe
(307507, 94)

```
----------
TARGET repartition in the dataframe :
0    282682
1     24825
Name: TARGET, dtype: int64
----------
pourcentage target 1/0 : 8.781952865764357 %
```



Partie II – Choix du modèle et du score d'évaluation

Image : canstockphoto

II – Score d'évaluation

ROC AUC > f1
(receiver operating characteristic > accuracy)

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Score :

100 % de 0

→ ***accuracy*** **globale : 91,2 %**

→ ***accuracy*** **classe majoritaire : 100 %**

→ **accuracy classe minoritaire : 0 %**

II – Score d'évaluation

ROC AUC > f1
(receiver operating characteristic > accuracy)

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

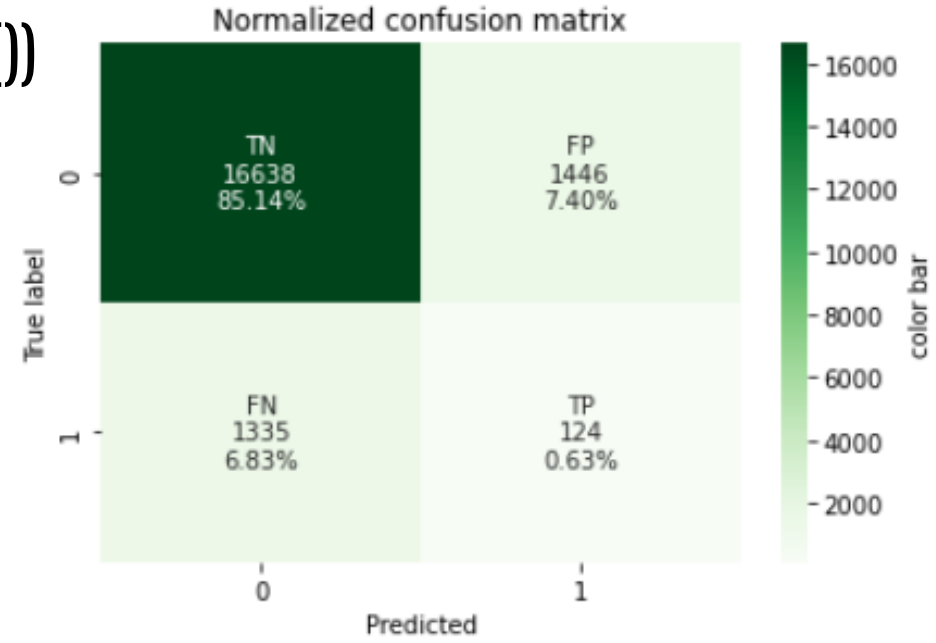
$$FPR = \frac{FP}{FP + TN} \qquad precision\ (TPR) = \frac{TP}{TP + FP} \qquad recall = \frac{TP}{TP + FN} \qquad F_\beta = \frac{(1 + \beta^2)\ * precision\ * recall}{(\beta^2 * precision) + recall}$$

II – Score d'évaluation

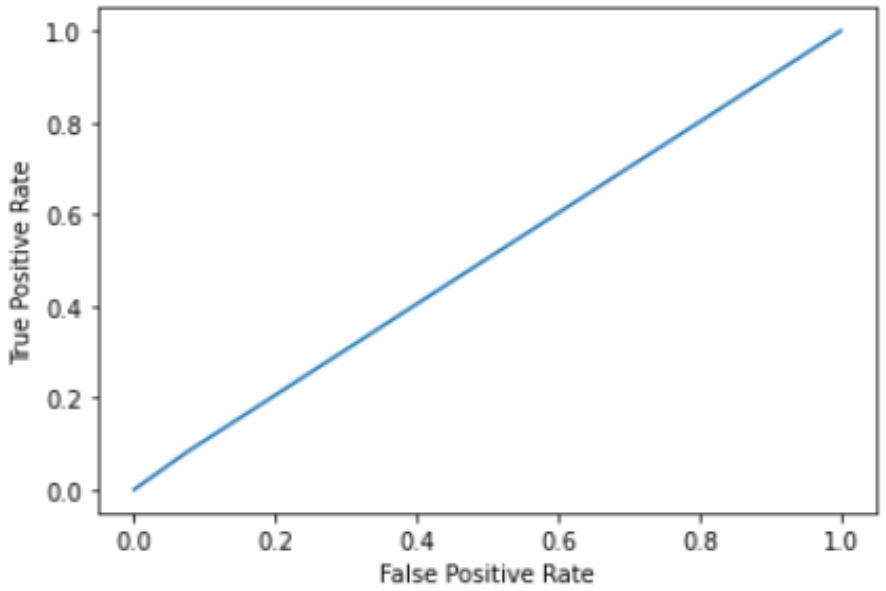
ROC AUC > f1
(receiver operating characteristic > accuracy)

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Baseline
(DummyClassifier())



ROC curve



II – Modèles et traitement du déséquilibre

Data prepation
Pipeline (StandardScaler(), MinMaxScaler(), {SMOTE}, model())

Type of models
- Algorithmes linéaires
- Algorithmes non-linéaires
- Algorithmes ensemblistes

Gestion du déséquilibre
- Rien
- class_weight (« cost sensitive »)
- SMOTE (Synthetic Minority Oversampling Technique)

II – LogisticRegression unbalanced treatment

Evaluation des modèles

cross_val_score(RepeatedStratifiedKFold(n_splits=10, n_repeats=3)

	model	scoring	score_trains	std_trains	fitting_time	std_fit	predict_time	score_test	TPR	FNR
0	LR	roc_auc	0.500798	0.038979	16.081664	0.404100	(14.007, sec)	0.918865	0.999383	0.080618
1	LR_weight	roc_auc	0.672930	0.018072	14.453520	0.186147	(12.42, sec)	0.596369	0.590039	0.046950
2	LR_SMOTE	roc_auc	0.685561	0.002308	714.738109	8.851074	(1823.383, sec)	0.577305	0.570291	0.050062
3	LR	make_scorer(fbeta_score, beta=2)	0.001620	0.000882	15.905251	0.384689	(14.018, sec)	0.918865	0.999383	0.080618
4	LR_weight	make_scorer(fbeta_score, beta=2)	0.352641	0.017613	13.732434	0.181817	(12.523, sec)	0.596369	0.590039	0.046950
5	LR_SMOTE	make_scorer(fbeta_score, beta=2)	0.365627	0.005887	710.028121	10.947881	(1807.287, sec)	0.598241	0.590780	0.044897
6	LR	make_scorer(fonction_metier)	-0.998679	0.000728	15.653084	0.390384	(15.175, sec)	0.918865	0.999383	0.080618
7	LR_weight	make_scorer(fonction_metier)	-0.372375	0.032243	13.468927	0.186016	(12.817, sec)	0.596369	0.590039	0.046950
8	LR_SMOTE	make_scorer(fonction_metier)	-0.340377	0.001971	685.754411	15.263532	(1905.344, sec)	0.577929	0.567761	0.045148

II – Présélection

Evaluation des modèles

cross_val_score(RepeatedStratifiedKFold(n_splits=10, n_repeats=3)

Score : roc_auc

LR_B : Basic Logistic Regression

All the other models include a pipeline with SMOTE

LR : Logistic Regression

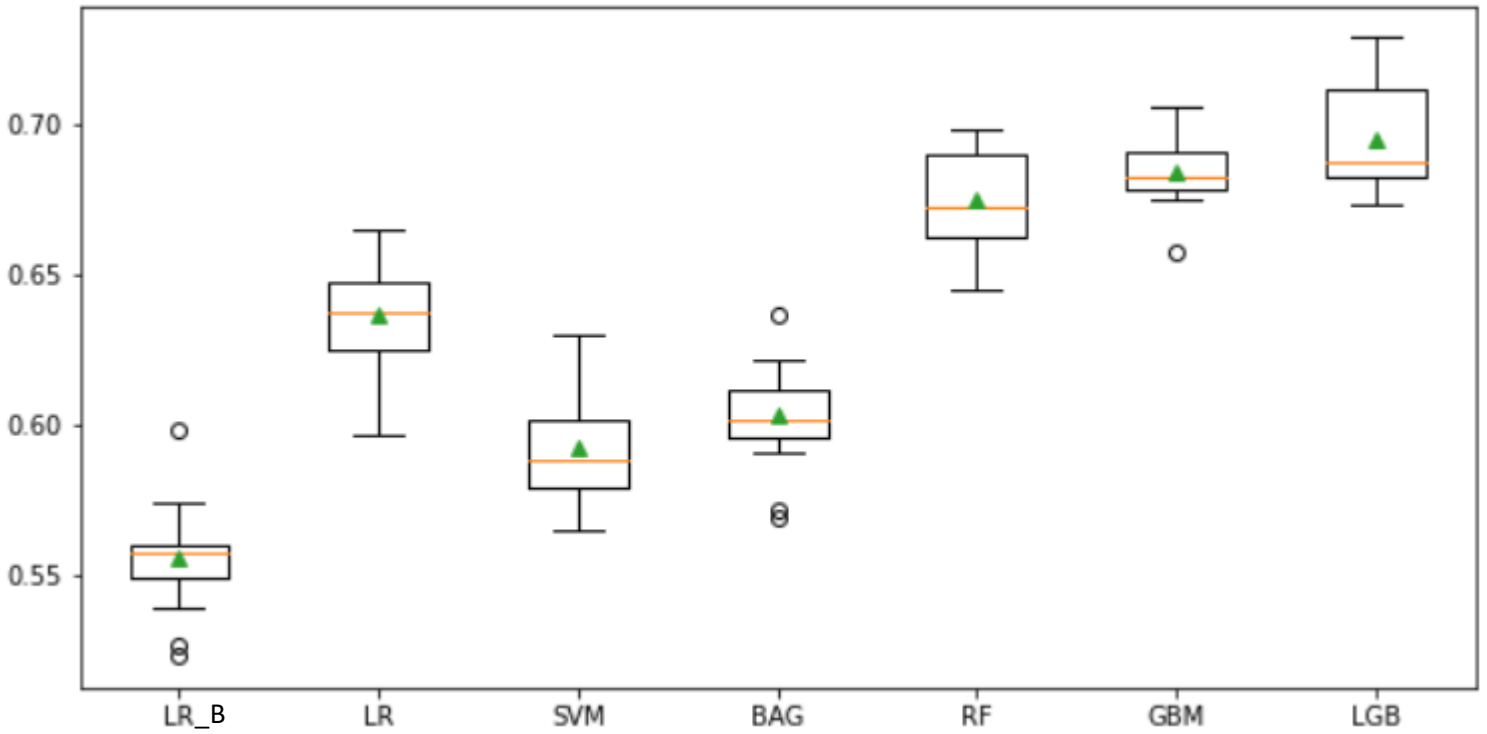
SVM : support vecteur machine cost sensitive

BAG : bagging

RF : Random Forest

GBM : Gradient boosting

LGB_B : Light gradient boosting



II – Présélection

Evaluation des modèles

cross_val_score(RepeatedStratifiedKFold(n_splits=10, n_repeats=3)

Score : custom

LR_B : Basic Logistic Regression

All the other models include a pipeline with SMOTE

LR : Logistic Regression

SVM : support vecteur machine cost sensitive

BAG : bagging

RF : Random Forest

GBM : Gradient boosting

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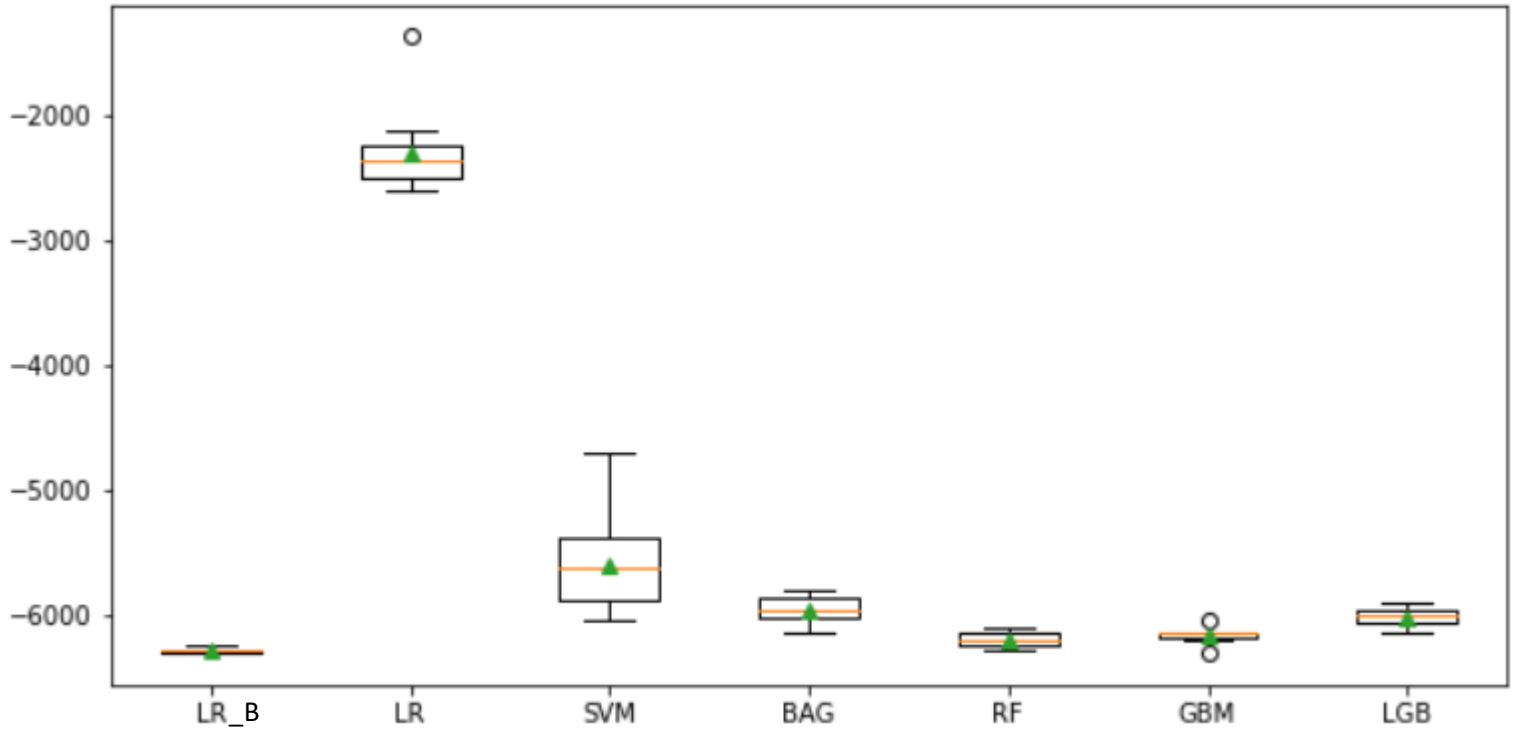


II – Présélection

Evaluation des modèles

cross_val_score(RepeatedStratifiedKFold(n_splits=10, n_repeats=3)

Score : fbeta

LR_B : Basic Logistic Regression

All the other models include a pipeline with SMOTE

LR : Logistic Regression

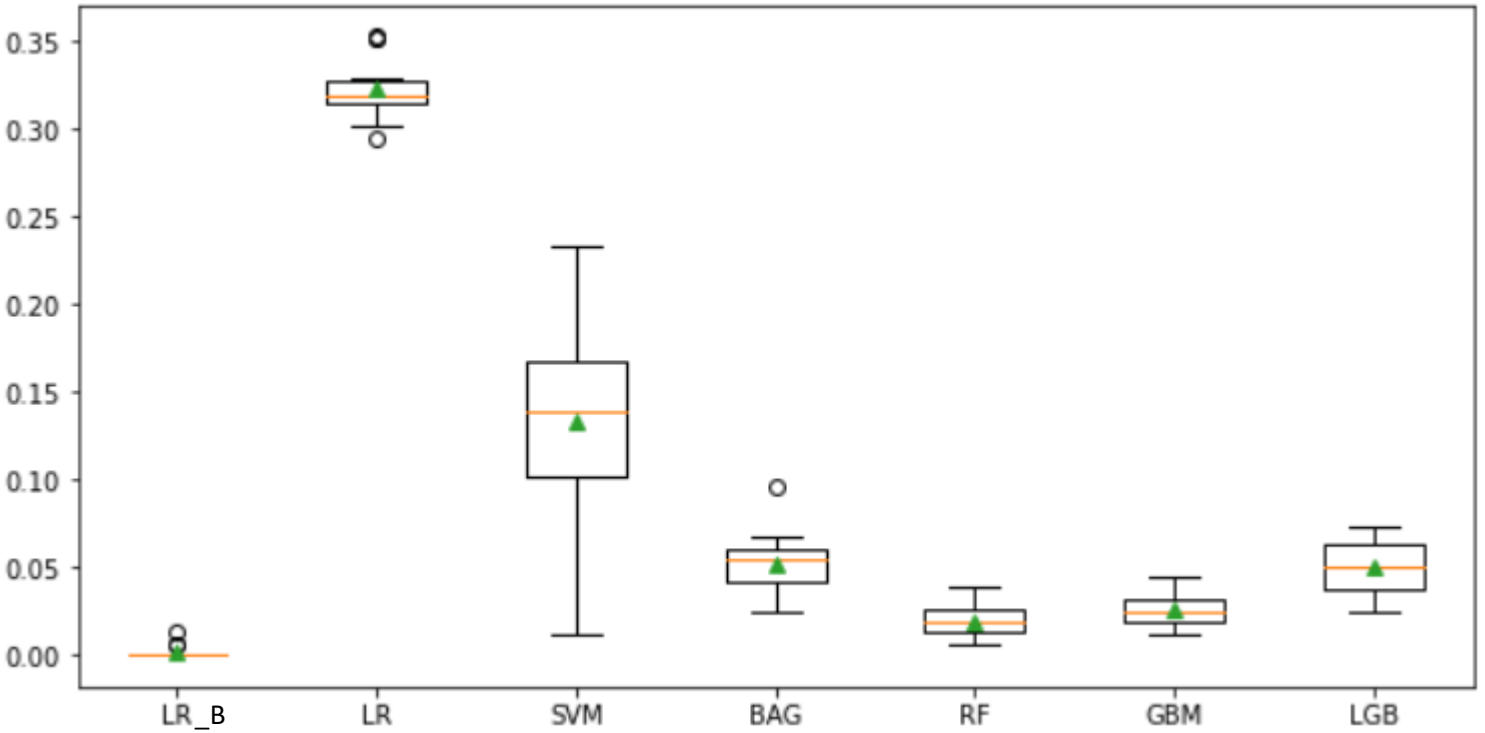
SVM : support vecteur machine cost sensitive

BAG : bagging

RF : Random Forest

GBM : Gradient boosting

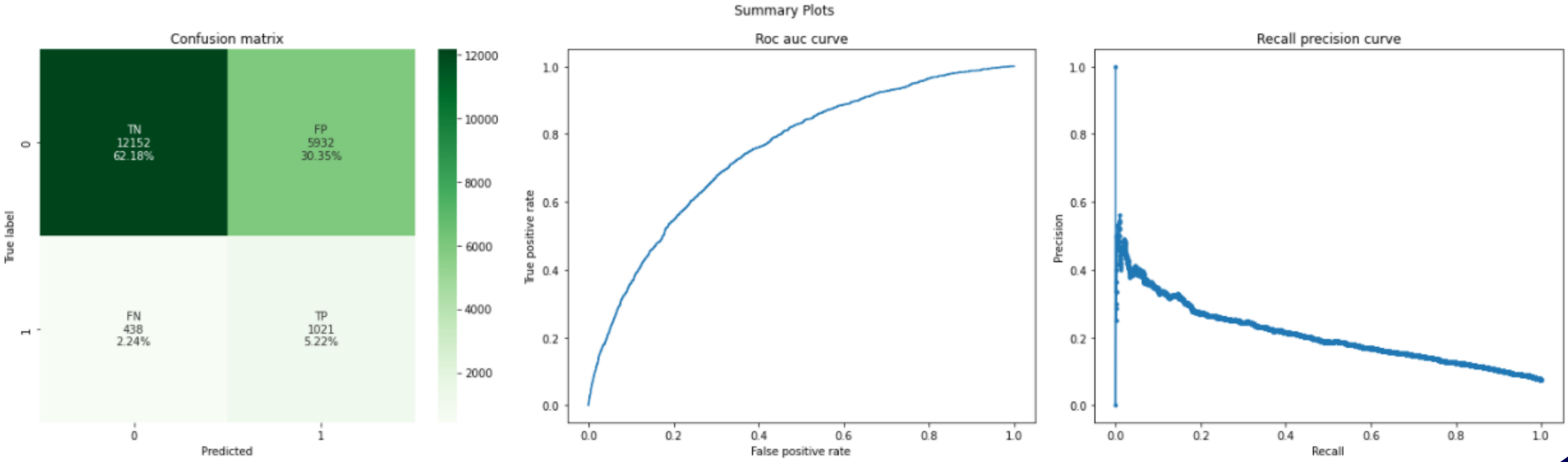
LGB_B : Light gradient boosting



II – Réglages des Hyperparamètres

Evaluation des modèles

GridSearchCV(model(), parameters)

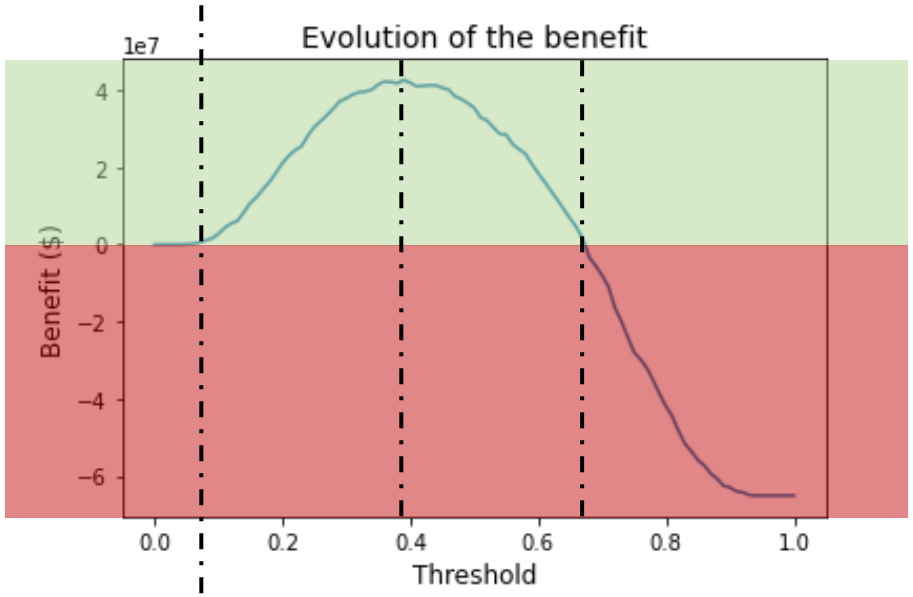


II – Fonction coût et retours métier

1. Fonction coût métier : $(\frac{TP}{FN+TP} - 33 * \frac{FN}{FN+TP})/32$

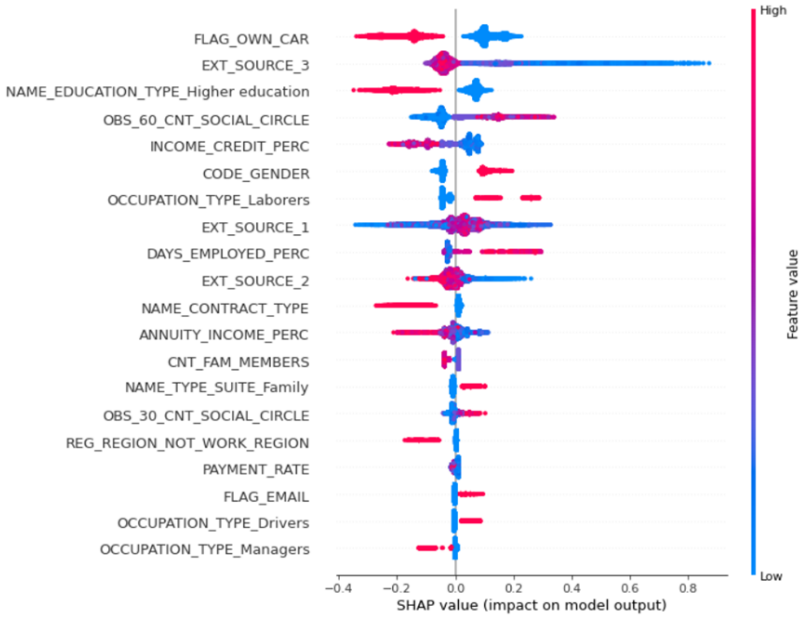
2. Optimisation des hyperparamètres

3. Choix du seuil



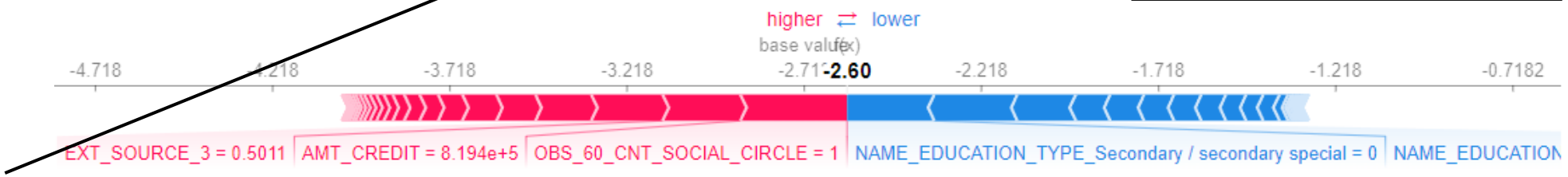
II – Feature importance

SHAP (Shapley Additive exPlanations)



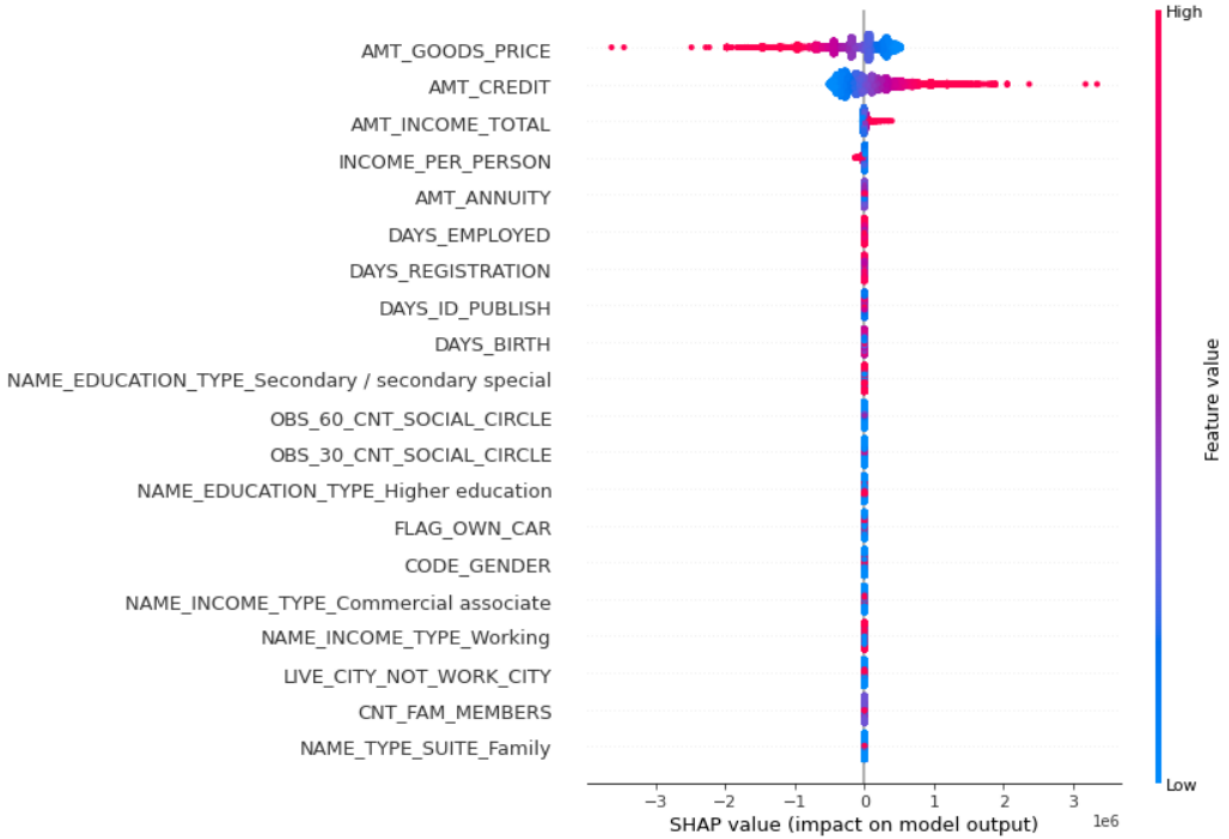
Approche globale

Approche locale

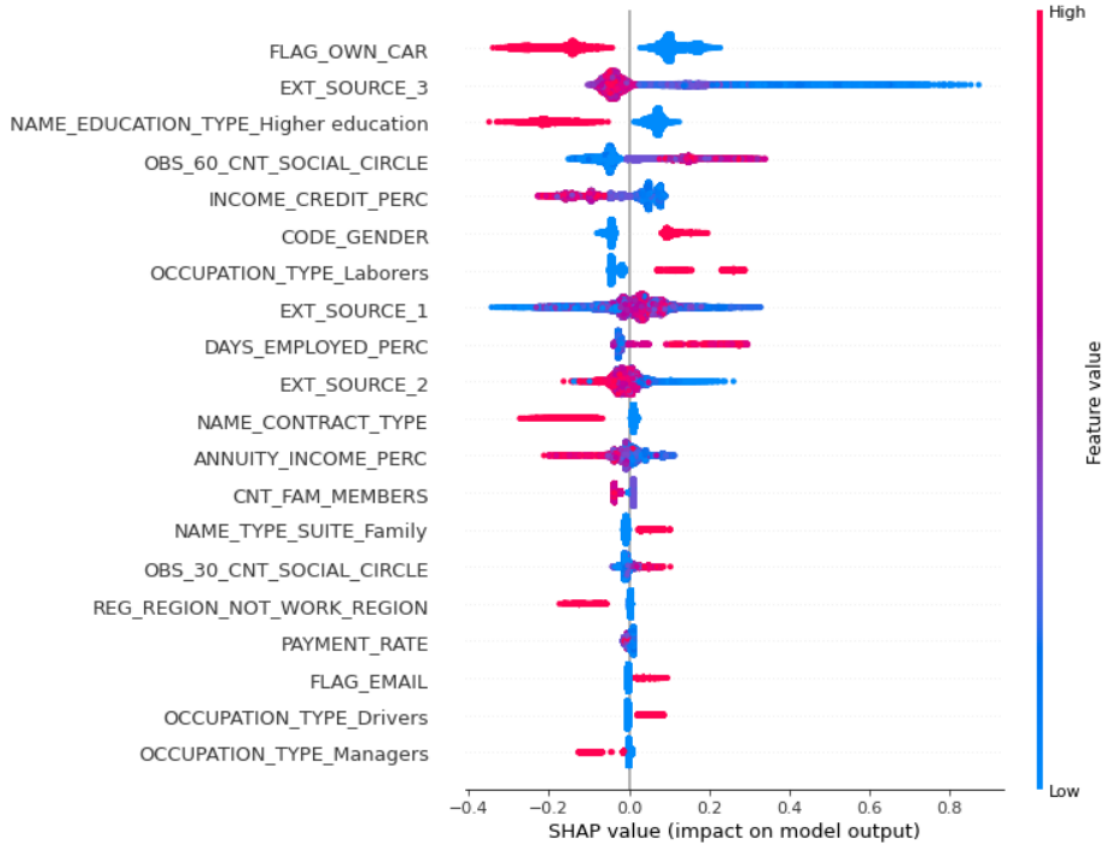


II – Interprétation du modèle

Logistic Reg



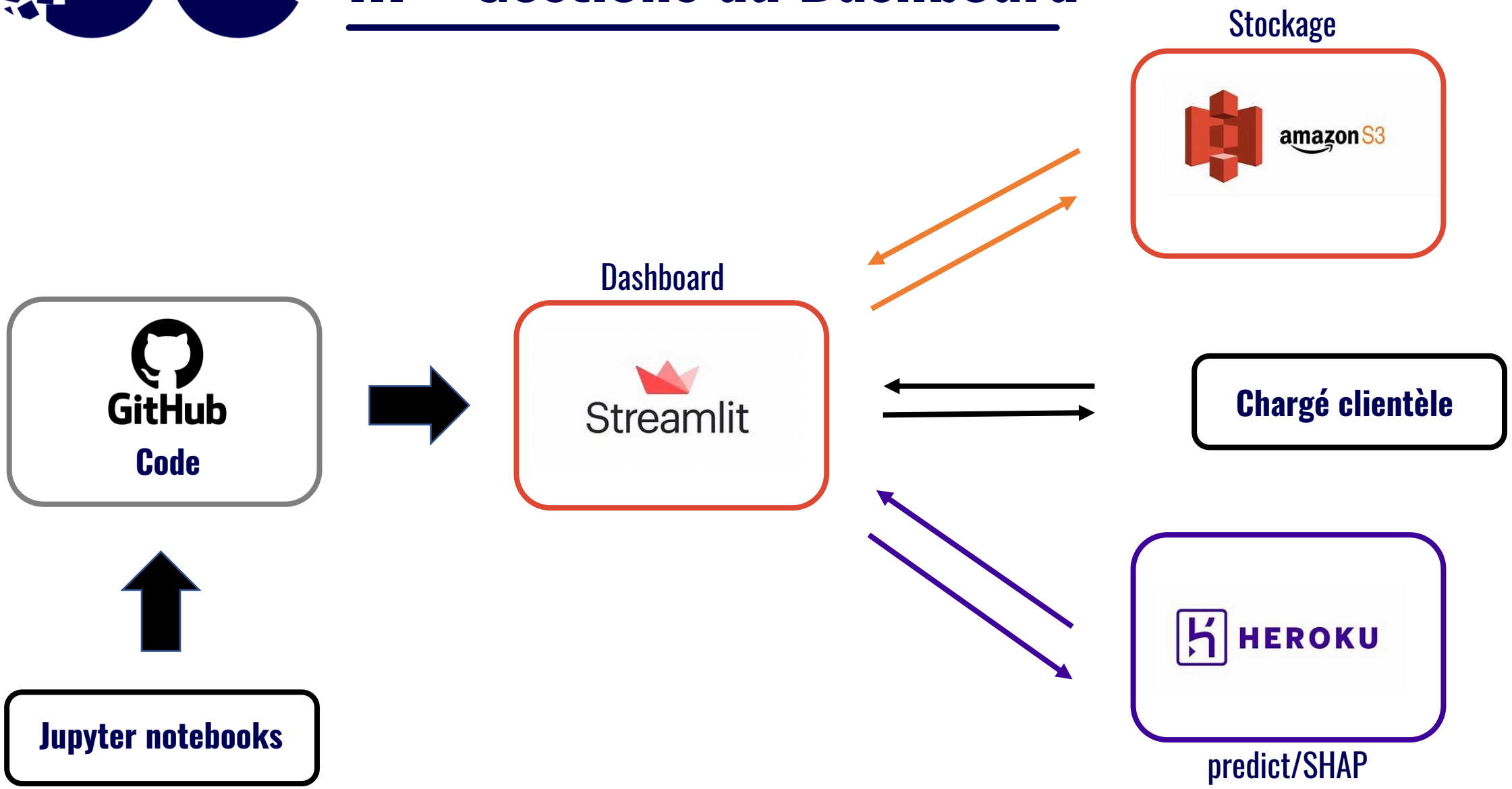
LGBM



Partie III – Présentation du Dashboard

Image : managersenmission

III – Gestions du Dashboard



III – Présentation du Dashboard

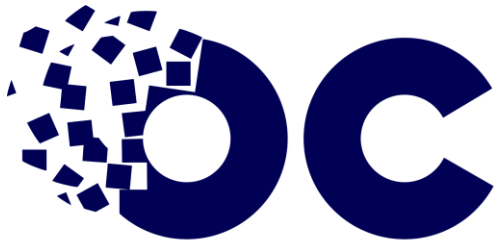
III – Note méthodologique

- La méthodologie d'entraînement du modèle
- La fonction coût métier, l'algorithme d'optimisation et la métrique d'évaluation
- L’interprétabilité globale et locale du modèle
- Les limites et les améliorations possibles

Conclusion

- Réalisation d'un dashbord interactif et d'une API de prédiction

- Avec De multiples pistes d'amélioration
  - Inclusion de toutes les BDD
  - Plus de modèles de ML à tester
  - Prétraitement spécifiques à chaque modèle
  - Approfondissement des techniques SMOTE
  - Retours métiers

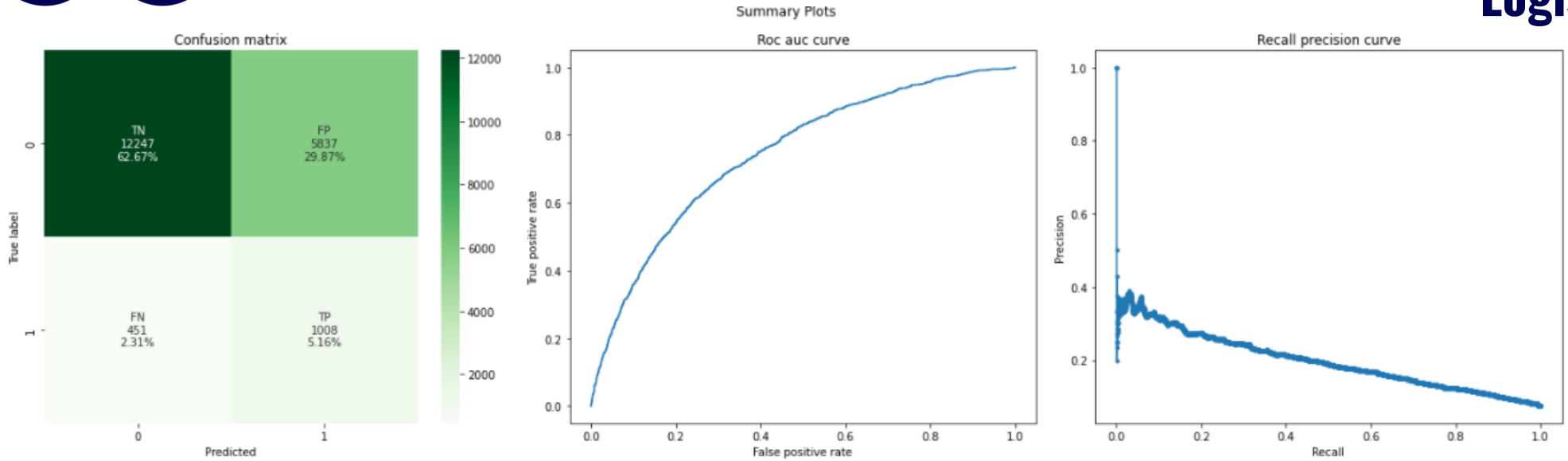


Fin

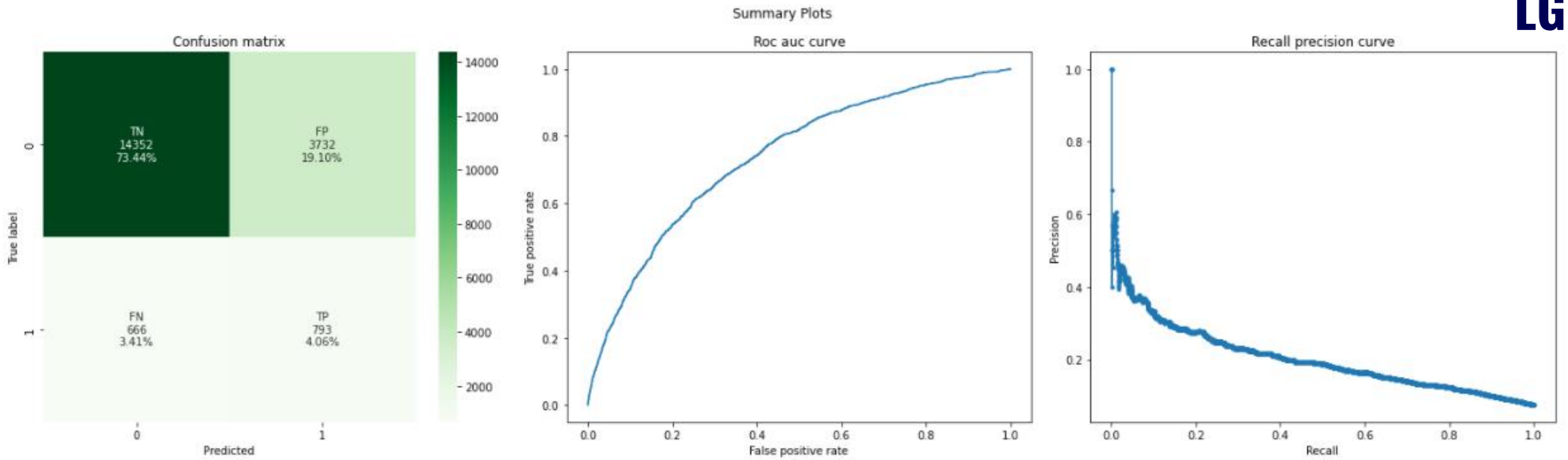
Merci de votre attention !

II – Interprétation du modèle

Logistic Reg



LGBM



II – Réglages des Hyperparamètres