zmhc2iocc

September 19, 2025

[1]:
```
from pathlib import Path
import pandas as pd
import numpy as np

# Dossiers
DATA_RAW = Path("data/raw")
DATA_PROC = Path("data/processed")
MODELS_DIR = Path("models")
for p in [DATA_RAW, DATA_PROC, MODELS_DIR]:
    p.mkdir(parents=True, exist_ok=True)

print("OK dossiers:", DATA_RAW.resolve(), DATA_PROC.resolve(), MODELS_DIR.
 ↪resolve())
```

```
OK dossiers: /home/nicolasd/code/nicolasdestrac/OpenClassrooms/Projet_7/data/raw
/home/nicolasd/code/nicolasdestrac/OpenClassrooms/Projet_7/data/processed
/home/nicolasd/code/nicolasdestrac/OpenClassrooms/Projet_7/models
```

[2]:
```
# Visu
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno

# ML
from sklearn.model_selection import train_test_split, StratifiedKFold,␣
 ↪GridSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import roc_auc_score, roc_curve, confusion_matrix,␣
 ↪classification_report

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import lightgbm as lgb
```

```
# Explicabilité
import shap

# MLOps
import mlflow
import os
import mlflow.sklearn
from mlflow.tracking import MlflowClient
from mlflow.models import infer_signature
import joblib
import json
from dotenv import load_dotenv
load_dotenv()

# Réglages d'affichage
%matplotlib inline
```

```
/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update
jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

[3]:
```
mlflow.set_tracking_uri(os.getenv("MLFLOW_TRACKING_URI", "databricks"))
mlflow.set_registry_uri(os.getenv("MLFLOW_TRACKING_URI", "databricks"))
exp_path = os.getenv("MLFLOW_EXPERIMENT", "/Users/nicolas.destrac@gmail.com/
 ↪projet7_scoring")
mlflow.set_experiment(exp_path)

# contrôle
client = MlflowClient()
exp = client.get_experiment_by_name(exp_path)
print("Tracking URI ->", mlflow.get_tracking_uri())
print("Experiment    ->", exp.name)
print("Artifact Loc  ->", exp.artifact_location)
```

```
Tracking URI -> databricks
Experiment    -> /Users/nicolas.destrac@gmail.com/projet7_scoring
Artifact Loc  -> dbfs:/databricks/mlflow-tracking/637345509737061
```

[4]:
```
train_path = DATA_RAW / "application_train.csv"
test_path  = DATA_RAW / "application_test.csv"

assert train_path.exists(), f"Manque {train_path} (place dans data/raw)"
assert test_path.exists(),  f"Manque {test_path} (place dans data/raw)"

train = pd.read_csv(train_path)
```

```
test  = pd.read_csv(test_path)

train.shape, test.shape
```

[4]: ((307511, 122), (48744, 121))

[5]:
```
# Verification que la cible ne soit que dans le train
col_list = [col for col in list(train.columns) if col not in list(test.columns)]
col_list
```

[5]: ['TARGET']

[6]:
```
train.head(3)
```

[6]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	…	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
0	100002	1	Cash loans	M	N	Y	0	202500.0	406597.5	24700.5	…	0	0	0	0	0.0	0.0	0.0	0.0	0.0	1.0
1	100003	0	Cash loans	F	N	N	0	270000.0	1293502.5	35698.5	…	0	0	0	0	0.0	0.0	0.0	0.0	0.0	0.0
2	100004	0	Revolving loans	M	Y	Y	0	67500.0	135000.0	6750.0	…	0	0	0	0	0.0	0.0	0.0	0.0	0.0	0.0

[3 rows x 122 columns]

[7]:
```
display(train.dtypes.value_counts())

# Stats numériques (aperçu)
display(train.describe(include="number").T.head(15))

# % de NaN
na_pct = train.isna().mean().sort_values(ascending=False).
 ↪to_frame("missing_rate")
na_pct.head(20)
```

```
float64    65
int64      41
object     16
Name: count, dtype: int64
```

	count	mean	std	\
SK_ID_CURR	307511.0	278180.518577	102790.175348	
TARGET	307511.0	0.080729	0.272419	
CNT_CHILDREN	307511.0	0.417052	0.722121	
AMT_INCOME_TOTAL	307511.0	168797.919297	237123.146279	
AMT_CREDIT	307511.0	599025.999706	402490.776996	
AMT_ANNUITY	307499.0	27108.573909	14493.737315	
AMT_GOODS_PRICE	307233.0	538396.207429	369446.460540	
REGION_POPULATION_RELATIVE	307511.0	0.020868	0.013831	
DAYS_BIRTH	307511.0	-16036.995067	4363.988632	
DAYS_EMPLOYED	307511.0	63815.045904	141275.766519	
DAYS_REGISTRATION	307511.0	-4986.120328	3522.886321	
DAYS_ID_PUBLISH	307511.0	-2994.202373	1509.450419	
OWN_CAR_AGE	104582.0	12.061091	11.944812	
FLAG_MOBIL	307511.0	0.999997	0.001803	
FLAG_EMP_PHONE	307511.0	0.819889	0.384280	

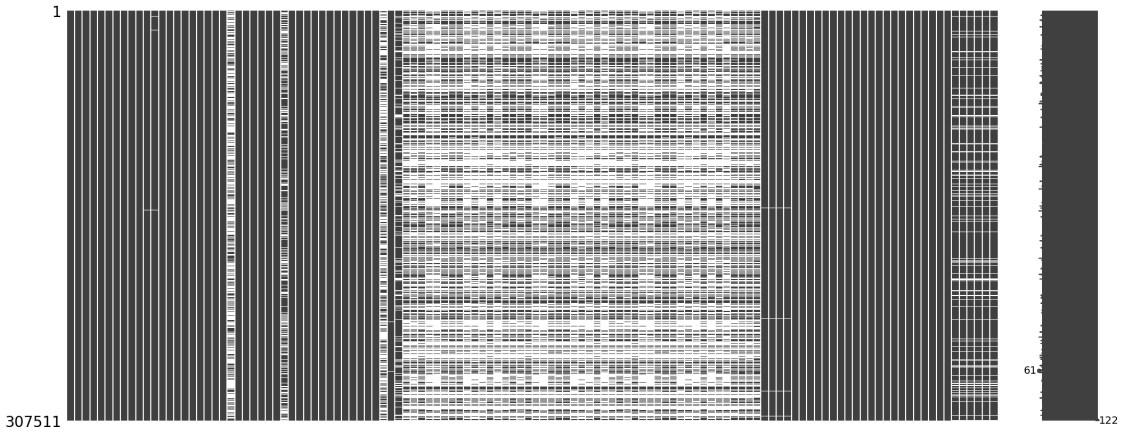
	min	25%	50%	\
SK_ID_CURR	100002.00000	189145.500000	278202.00000	
TARGET	0.00000	0.000000	0.00000	
CNT_CHILDREN	0.00000	0.000000	0.00000	
AMT_INCOME_TOTAL	25650.00000	112500.000000	147150.00000	
AMT_CREDIT	45000.00000	270000.000000	513531.00000	
AMT_ANNUITY	1615.50000	16524.000000	24903.00000	
AMT_GOODS_PRICE	40500.00000	238500.000000	450000.00000	
REGION_POPULATION_RELATIVE	0.00029	0.010006	0.01885	
DAYS_BIRTH	-25229.00000	-19682.000000	-15750.00000	
DAYS_EMPLOYED	-17912.00000	-2760.000000	-1213.00000	
DAYS_REGISTRATION	-24672.00000	-7479.500000	-4504.00000	
DAYS_ID_PUBLISH	-7197.00000	-4299.000000	-3254.00000	
OWN_CAR_AGE	0.00000	5.000000	9.00000	
FLAG_MOBIL	0.00000	1.000000	1.00000	
FLAG_EMP_PHONE	0.00000	1.000000	1.00000	

	75%	max
SK_ID_CURR	367142.500000	4.562550e+05
TARGET	0.000000	1.000000e+00
CNT_CHILDREN	1.000000	1.900000e+01
AMT_INCOME_TOTAL	202500.000000	1.170000e+08
AMT_CREDIT	808650.000000	4.050000e+06
AMT_ANNUITY	34596.000000	2.580255e+05
AMT_GOODS_PRICE	679500.000000	4.050000e+06
REGION_POPULATION_RELATIVE	0.028663	7.250800e-02
DAYS_BIRTH	-12413.000000	-7.489000e+03
DAYS_EMPLOYED	-289.000000	3.652430e+05
DAYS_REGISTRATION	-2010.000000	0.000000e+00
DAYS_ID_PUBLISH	-1720.000000	0.000000e+00
OWN_CAR_AGE	15.000000	9.100000e+01
FLAG_MOBIL	1.000000	1.000000e+00
FLAG_EMP_PHONE	1.000000	1.000000e+00

[7]:

	missing_rate
COMMONAREA_AVG	0.698723
COMMONAREA_MODE	0.698723
COMMONAREA_MEDI	0.698723
NONLIVINGAPARTMENTS_MEDI	0.694330
NONLIVINGAPARTMENTS_MODE	0.694330
NONLIVINGAPARTMENTS_AVG	0.694330
FONDKAPREMONT_MODE	0.683862
LIVINGAPARTMENTS_AVG	0.683550
LIVINGAPARTMENTS_MEDI	0.683550
LIVINGAPARTMENTS_MODE	0.683550
FLOORSMIN_MODE	0.678486
FLOORSMIN_AVG	0.678486
FLOORSMIN_MEDI	0.678486
YEARS_BUILD_AVG	0.664978
YEARS_BUILD_MODE	0.664978
YEARS_BUILD_MEDI	0.664978
OWN_CAR_AGE	0.659908
LANDAREA_MEDI	0.593767
LANDAREA_AVG	0.593767
LANDAREA_MODE	0.593767

[8]:
```
msno.matrix(train);
```



[9]:
```
target_counts = train["TARGET"].value_counts()
ax = target_counts.plot(kind="bar")
ax.set_title("Distribution de TARGET"); ax.set_xlabel("Classe"); ax.
 ↪set_ylabel("Effectif")
plt.show()

(target_counts/len(train)).round(4)
```

[9]:
```
TARGET
0    0.9193
1    0.0807
Name: count, dtype: float64
```

[10]:
```
# Feature engineering
for df in (train, test):
    df.loc[df["DAYS_EMPLOYED"] > 365000, "DAYS_EMPLOYED"] = np.nan
    df["AGE_YEARS"] = (-df["DAYS_BIRTH"] / 365).astype(float)
    df["EMP_YEARS"] = (-df["DAYS_EMPLOYED"] / 365)

    df["CREDIT_INCOME_RATIO"] = df["AMT_CREDIT"] / (df["AMT_INCOME_TOTAL"] +␣
 ↪1e-6)
    df["ANNUITY_INCOME_RATIO"] = df["AMT_ANNUITY"] / (df["AMT_INCOME_TOTAL"] +␣
 ↪1e-6)
    df["ANNUITY_CREDIT_RATIO"] = df["AMT_ANNUITY"] / (df["AMT_CREDIT"] + 1e-6)
    df["GOODS_CREDIT_RATIO"]  = df["AMT_GOODS_PRICE"] / (df["AMT_CREDIT"] +␣
 ↪1e-6)

    for a,b in [("EXT_SOURCE_1","EXT_SOURCE_2"),␣
 ↪("EXT_SOURCE_2","EXT_SOURCE_3"), ("EXT_SOURCE_1","EXT_SOURCE_3")]:
        if a in df.columns and b in df.columns:
            df[f"{a}_x_{b}"]    = df[a] * df[b]
            df[f"{a}_plus_{b}"] = df[a] + df[b]
```

[11]:
```
y = train["TARGET"]
X = train.drop(columns=["TARGET"])

X_train, X_valid, y_train, y_valid = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
X_train.shape, X_valid.shape
```

[11]:
```
((246008, 133), (61503, 133))
```

[12]:
```
num_cols = X_train.select_dtypes(include=["int64","float64"]).columns.tolist()
cat_cols = X_train.select_dtypes(include=["object","category","bool"]).columns.
 ↪tolist()

numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler(with_mean=False)),  # compat. sparse
])
```

```
categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(handle_unknown="ignore"))
])

preprocessor = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, num_cols),
        ("cat", categorical_transformer, cat_cols),
    ]
)

len(num_cols), len(cat_cols)
```

[12]: (117, 16)

[13]:
```
def eval_auc(model, X_tr, y_tr, X_va, y_va):
    p_tr = model.predict_proba(X_tr)[:,1]
    p_va = model.predict_proba(X_va)[:,1]
    return roc_auc_score(y_tr, p_tr), roc_auc_score(y_va, p_va)
```

[14]:
```
results = []

# 1) Logistic Regression (ponderation classes)
logreg = Pipeline(steps=[
    ("prep", preprocessor),
    ("clf", LogisticRegression(
        solver="saga",
        penalty="l2",
        max_iter=2000,
        class_weight="balanced",
        n_jobs=-1
    ))
])
logreg.fit(X_train, y_train)
auc_tr, auc_va = eval_auc(logreg, X_train, y_train, X_valid, y_valid)
results.append(("LogReg", auc_tr, auc_va))

# 2) RandomForest
rf = Pipeline(steps=[
    ("prep", preprocessor),
    ("clf", RandomForestClassifier(
        n_estimators=300, random_state=42, class_weight="balanced_subsample"
    ))
])
rf.fit(X_train, y_train)
auc_tr, auc_va = eval_auc(rf, X_train, y_train, X_valid, y_valid)
```

```
results.append(("RandomForest", auc_tr, auc_va))

# 3) LightGBM (params simples)
lgbm = Pipeline(steps=[
    ("prep", preprocessor),
    ("clf", lgb.LGBMClassifier(
        n_estimators=600, learning_rate=0.05, num_leaves=64,
        subsample=0.8, colsample_bytree=0.8, random_state=42
    ))
])
lgbm.fit(X_train, y_train)
auc_tr, auc_va = eval_auc(lgbm, X_train, y_train, X_valid, y_valid)
results.append(("LightGBM", auc_tr, auc_va))

pd.DataFrame(results, columns=["model","auc_train","auc_valid"]).
 ↪sort_values("auc_valid", ascending=False)
```

```
/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/linear_model/_sag.py:348: ConvergenceWarning: The max_iter was
reached which means the coef_ did not converge
  warnings.warn(

[LightGBM] [Info] Number of positive: 19860, number of negative: 226148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.124523 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 14759
[LightGBM] [Info] Number of data points in the train set: 246008, number of used
features: 246
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432482
[LightGBM] [Info] Start training from score -2.432482

/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(
/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(
```

[14]:

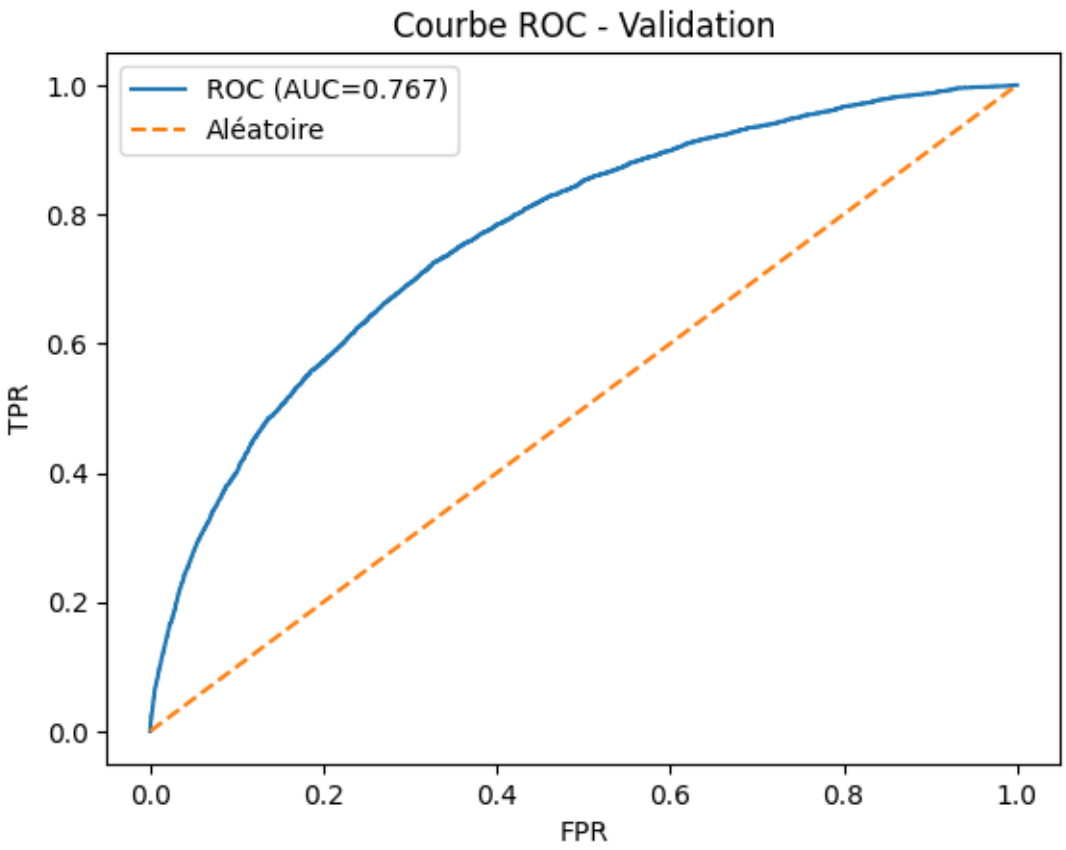
	model	auc_train	auc_valid
2	LightGBM	0.930568	0.766911
0	LogReg	0.751681	0.751054
1	RandomForest	1.000000	0.745732

[15]:
```
COST_FN = 10.0  # coût faux négatif (accorder un mauvais client)
COST_FP = 1.0   # coût faux positif (refuser un bon client)
```

```
def business_cost(y_true, y_prob, threshold=0.5, cost_fn=COST_FN,␣
 ↪cost_fp=COST_FP):
    y_pred = (y_prob >= threshold).astype(int)
    tn, fp, fn, tp = confusion_matrix(y_true, y_pred, labels=[0,1]).ravel()
    return fn * cost_fn + fp * cost_fp

def find_best_threshold(y_true, y_prob, cost_fn=COST_FN, cost_fp=COST_FP):
    thresholds = np.linspace(0.01, 0.99, 99)
    costs = [business_cost(y_true, y_prob, t, cost_fn, cost_fp) for t in␣
 ↪thresholds]
    best_idx = int(np.argmin(costs))
    return float(thresholds[best_idx]), float(costs[best_idx])

# On prend le meilleur modèle AUC
best_model = lgbm
y_valid_prob = best_model.predict_proba(X_valid)[:,1]
best_th, best_cost = find_best_threshold(y_valid, y_valid_prob)
auc_val = roc_auc_score(y_valid, y_valid_prob)

print(f"AUC valid = {auc_val:.4f}")
print(f"Seuil métier optimal = {best_th:.3f} | Coût validation = {best_cost:.
 ↪1f}")
```

```
/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(

AUC valid = 0.7669
Seuil métier optimal = 0.080 | Coût validation = 32058.0
```

[16]:
```
fpr, tpr, thr = roc_curve(y_valid, y_valid_prob)
plt.figure()
plt.plot(fpr, tpr, label=f"ROC (AUC={auc_val:.3f})")
plt.plot([0,1],[0,1],"--", label="Aléatoire")
plt.title("Courbe ROC - Validation")
plt.xlabel("FPR"); plt.ylabel("TPR"); plt.legend(); plt.show()

print(f"Seuil choisi (métier) = {best_th:.3f}")
```




```
Seuil choisi (métier) = 0.080
```

[17]:
```
def mem_mb(df):
    return df.memory_usage(deep=True).sum() / 1024**2

print(f"RAM train: {mem_mb(train):.1f} MB | RAM test: {mem_mb(test):.1f} MB")

dtype_counts_train = train.dtypes.value_counts()
dtype_counts_test  = test.dtypes.value_counts()
dtype_counts_train, dtype_counts_test
```

```
RAM train: 564.8 MB | RAM test: 89.2 MB
```

[17]:
```
(float64    78
 int64      40
 object     16
 Name: count, dtype: int64,
 float64    78
 int64      39
 object     16
```

```
Name: count, dtype: int64)
```

[18]:
```
na_pct = train.isna().mean().sort_values(ascending=False).
  ↪to_frame("missing_rate")
na_pct.head(25)
```

[18]:

	missing_rate
COMMONAREA_AVG	0.698723
COMMONAREA_MODE	0.698723
COMMONAREA_MEDI	0.698723
NONLIVINGAPARTMENTS_AVG	0.694330
NONLIVINGAPARTMENTS_MEDI	0.694330
NONLIVINGAPARTMENTS_MODE	0.694330
FONDKAPREMONT_MODE	0.683862
LIVINGAPARTMENTS_MEDI	0.683550
LIVINGAPARTMENTS_AVG	0.683550
LIVINGAPARTMENTS_MODE	0.683550
FLOORSMIN_MODE	0.678486
FLOORSMIN_AVG	0.678486
FLOORSMIN_MEDI	0.678486
YEARS_BUILD_MEDI	0.664978
YEARS_BUILD_MODE	0.664978
YEARS_BUILD_AVG	0.664978
OWN_CAR_AGE	0.659908
EXT_SOURCE_1_x_EXT_SOURCE_3	0.643128
EXT_SOURCE_1_plus_EXT_SOURCE_3	0.643128
LANDAREA_AVG	0.593767
LANDAREA_MEDI	0.593767
LANDAREA_MODE	0.593767
BASEMENTAREA_AVG	0.585160
BASEMENTAREA_MEDI	0.585160
BASEMENTAREA_MODE	0.585160

[19]:
```
def oof_auc_and_cost(model, X, y, cost_fn=COST_FN, cost_fp=COST_FP, n_splits=5):
    skf = StratifiedKFold(n_splits=n_splits, shuffle=True, random_state=42)
    oof_prob = np.zeros(len(y))
    for tr, va in skf.split(X, y):
        model.fit(X.iloc[tr], y.iloc[tr])
        oof_prob[va] = model.predict_proba(X.iloc[va])[:,1]
    auc = roc_auc_score(y, oof_prob)
    ths = np.linspace(0.01, 0.99, 99)
    def cost_at(t):
        y_pred = (oof_prob >= t).astype(int)
        fp = ((y_pred==1) & (y==0)).sum()
        fn = ((y_pred==0) & (y==1)).sum()
        return fn*cost_fn + fp*cost_fp
    costs = [(t, cost_at(t)) for t in ths]
```

```
    best_th, best_cost = min(costs, key=lambda x: x[1])
    return auc, best_th, best_cost, oof_prob
```

[21]:
```
auc_oof, th_oof, cost_oof, oof_prob = oof_auc_and_cost(best_model, X, y)
print(f"AUC OOF = {auc_oof:.4f} | Seuil OOF = {th_oof:.3f} | Coût OOF =␣
↪{cost_oof:.0f}")
```

```
[LightGBM] [Info] Number of positive: 19860, number of negative: 226148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.137074 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 14688
[LightGBM] [Info] Number of data points in the train set: 246008, number of used
features: 247
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432482
[LightGBM] [Info] Start training from score -2.432482

/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(

[LightGBM] [Info] Number of positive: 19860, number of negative: 226149
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.042665 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 14778
[LightGBM] [Info] Number of data points in the train set: 246009, number of used
features: 247
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432486
[LightGBM] [Info] Start training from score -2.432486

/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(

[LightGBM] [Info] Number of positive: 19860, number of negative: 226149
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.167464 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 14680
[LightGBM] [Info] Number of data points in the train set: 246009, number of used
features: 246
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432486
[LightGBM] [Info] Start training from score -2.432486

/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
```

```
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(

[LightGBM] [Info] Number of positive: 19860, number of negative: 226149
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.103762 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 14687
[LightGBM] [Info] Number of data points in the train set: 246009, number of used
features: 247
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432486
[LightGBM] [Info] Start training from score -2.432486

/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(

[LightGBM] [Info] Number of positive: 19860, number of negative: 226149
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.154609 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 14679
[LightGBM] [Info] Number of data points in the train set: 246009, number of used
features: 247
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432486
[LightGBM] [Info] Start training from score -2.432486

/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(

AUC OOF = 0.7634 | Seuil OOF = 0.080 | Coût OOF = 160830
```

[22]:
```python
# Normalisation du coût (pour 10 000 clients)
best_cost_norm = (best_cost / len(y_valid)) * 10_000
cost_oof_norm = (cost_oof / len(y)) * 10_000
```

[23]:
```python
print(f'Coût de validation train/test split : {best_cost_norm}')
print(f'Coût de validation OOF : {cost_oof_norm}')
```

```
Coût de validation train/test split : 5212.428662016488
Coût de validation OOF : 5230.056810975867
```

[24]:
```python
with mlflow.start_run(run_name="baseline_notebook_remote") as run:
    # Params & métriques
    mlflow.log_param("cost_fn", float(COST_FN))
    mlflow.log_param("cost_fp", float(COST_FP))
```

```
    mlflow.log_metric("auc_valid_or_oof", float(auc_val))
    mlflow.log_metric("best_threshold", float(best_th))
    mlflow.log_metric("business_cost", float(best_cost))

    # Artifacts
    Path("models").mkdir(exist_ok=True)
    joblib.dump(best_model, "models/scoring_model.joblib")
    with open("models/decision_threshold.json", "w") as f:
        json.dump({"threshold": float(best_th),
                   "cost_fn": float(COST_FN),
                   "cost_fp": float(COST_FP)}, f)
    mlflow.log_artifact("models/decision_threshold.json")

    # On ajoute une signature pour éviter le warning
    try:
        # petit échantillon pour la signature (X_valid existe déjà dans le␣
 ↪carnet)
        sig = infer_signature(X_valid.iloc[:100], best_model.
 ↪predict_proba(X_valid.iloc[:100])[:,1])
    except Exception:
        sig = None

    mlflow.sklearn.log_model(best_model, name="model", signature=sig)

    run_id = run.info.run_id
print("Run ID:", run_id)
```

```
/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(
/home/nicolasd/.pyenv/versions/3.10.6/envs/scoring_project7/lib/python3.10/site-
packages/mlflow/types/utils.py:452: UserWarning: Hint: Inferred schema contains
integer column(s). Integer columns in Python cannot represent missing values. If
your input data contains missing values at inference time, it will be encoded as
floats and will cause a schema enforcement error. The best way to avoid this
problem is to infer the model schema based on a realistic data sample (training
dataset) that includes missing values. Alternatively, you can declare integer
columns as doubles (float64) whenever these columns may have missing values. See
`Handling Integers With Missing Values
<https://www.mlflow.org/docs/latest/models.html#handling-integers-with-missing-
values>`_ for more details.
  warnings.warn(

 View run baseline_notebook_remote at: https://dbc-8fbfa9c5-63c4.cloud.databric
ks.com/ml/experiments/637345509737061/runs/c9de585dbbea4c52b5065f3fd9409ac8
 View experiment at:
https://dbc-8fbfa9c5-63c4.cloud.databricks.com/ml/experiments/637345509737061
```

Run ID: c9de585dbbea4c52b5065f3fd9409ac8