



Intro

Stack

Modèle : construction

Modèle : analyse

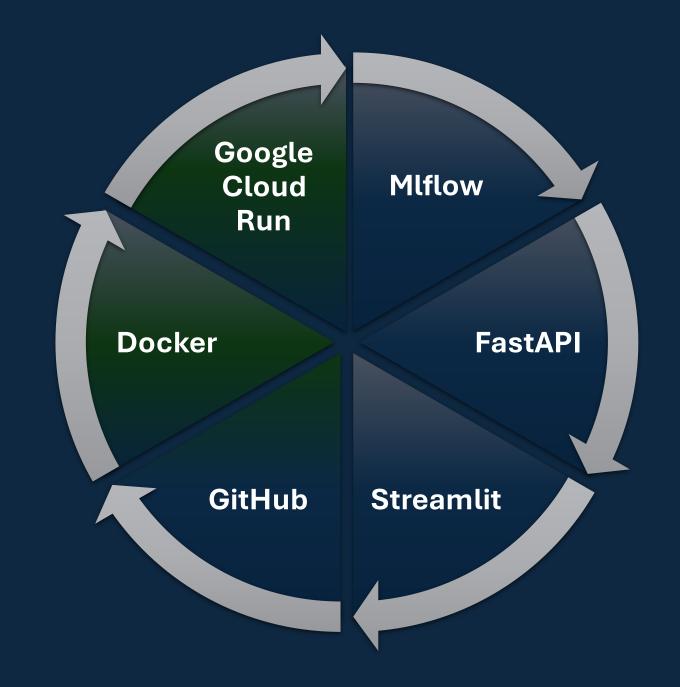
API

Déployement

Pour aller plus loin



Stack overview





8 fichiers

- application_test.parquet
- application_train.parquet
- bureau.parquet
- bureau_balance.parquet
- credit_card_balance.parquet
- installments_payments.parquet
- POS_CASH_balance.parquet
- previous_application.parquet

Group by	Aggreg
SK_ID	min
	max
	mean
	median
	sum

```
df_global.info()

<class 'pandas.core.frame.DataFrame'>
Index: 356251 entries, 0 to 356254
Columns: 896 entries, index to CC_COUNT
dtypes: bool(133), float64(704), int64(43), object(16)
memory usage: 2.1+ GB
```

```
df_global["TARGET"].value_counts(normalize=True)

TARGET
0.0 0.91927
1.0 0.08073

Name: proportion, dtype: float64
```

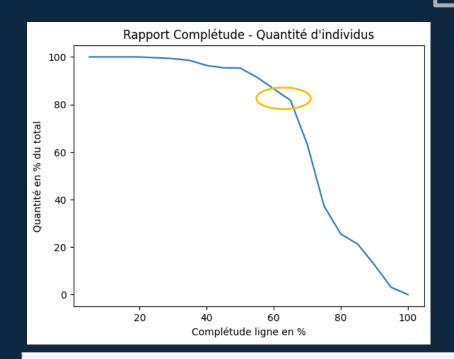
Construction modèle : overview

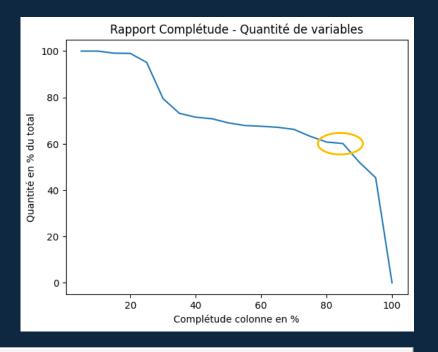
Expérience	Métrique	Réglages paramètres
Preprocess	ROC AUC	4
Process	ROC AUC	3 + Input
Algorithmes	ROC AUC + Custom	0
Tuning	Custom	2

```
"run_name": "median_80_c
"input_parquet": "C:\\Us
"output_parquet": "C:\\U
"completeness": 80,
   "impute": "median",
   "percent_outliers": 1,
   "target_col": "TARGET",
   "cv_threshold": 0.01
},
```

```
{
    "run_name": "Select40_
    "input_parquet": "C:\\
    "output_dir": "C:\\Use
    "n_select": 40,
    "cor_val": 0.7,
    "scaler": "robust",
    "target_col": "TARGET"
    "cache_dir": "C:\\User
},
```

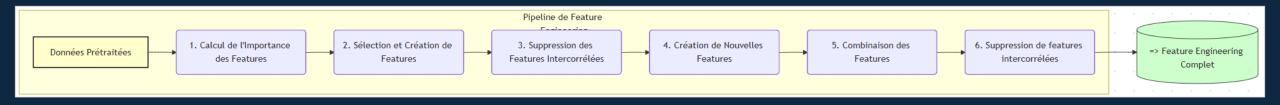
Preprocessing





					Metrics		Parameters			
	Run Name	Created	Duration	Source	final_feature_count	roc_auc = ↓	completeness	cv_threshold	impute	percent_outliers
	median_85_comp_0p5_ou	3 days ago	39.5s	preproce	508	0.747471868	85	0.05	median	0.5
	median_90_comp_0p2_ou	3 days ago	35.5s	preproce	438	0.745010426	90	0.1	median	0.2
# Drop rows based on completeness						0.738538930	80	0.01	median	1
<pre>row_completeness = (1 - df_processed.isnull().sum(axis=1) / df_processed.shape[1]) * 100 rows_to_drop_completeness = df_processed[row_completeness < completeness*0.5].index.tolist()</pre>						0.734446951	80	0.01	median	1
<pre>if rows_to_drop_completeness: df_processed.drop(index=rows_to_drop_completeness, inplace=True)</pre>						0.732860486	90	0.1	median	0.2
	<pre>if verbose: print(f"Dropped {len(rows_to_drop_completeness)} rows due to completeness < {completeness*0.5}%")</pre>						85	0.05	median	0.5

Processing



```
class FeatureEngineeringPipeline:
    def __init__(self, n_select: int = 50, cor_val: float = 0.7,
        self.n_select = n_select
        self.n_create = max(2, int(np.sqrt(n_select)))
        self.cor_val = cor_val
        self.target_col = target_col
```

```
importance_df = pd.DataFrame({
    'feature': X.columns,
    'metric1_spearman': spearman_corr,
    'metric2_mdi': rfc.feature_importances_,
    'metric3_product': spearman_corr * rfc.feature_importances_
}).sort_values(by='metric3_product', ascending=False).reset_index(drop=True)
```

				Metrics		Parameters		
Run Name	Created	Duration	Source	final_feature_coi	roc_auc_test <u>=</u> 1	cor_val	n_select	scaler
Select40_Cor50_Standard		17.8s	c:\Users\	26	0.708232735	0.5	40	standard
Select45_Cor55_Standard		18.5s	c:\Users\	27	0.710009252	0.55	45	standard
Select50_Cor60_Standard		20.9s	c:\Users\	31	0.713816272	0.6	50	standard
Select40_Cor70_Robust	3 days ago	39.8s	process.py	36	0.717219370	0.7	40	robust
Select60_Cor65_Robust	3 days ago	45.7s	process.py	41	0.718538204	0.65	60	robust
Select80_Cor60_Robust	3 days ago	50.9s	process.py	42	0.723408775	0.6	80	robust

Choix d'algorithme

				Metrics			
	Run Name	Cre	Duration	test_accuracy	test_auc	test_normalized_custom_score =	test_recall_at_best_t
	✓ ■ Group: gradient_boosting 6	-		0.71604155	0.71883838	2.2510152586876084 (aver	0.53755443134
	processed_s50_c60_stdgradient	(1.7min	0.873790117	0.718211127	4.024705556114052	0.261524822695
	processed_s80_c60_robustgradie	(3.6min	0.865385983	0.728525825	3.658911360851025	0.299623706491
	processed_s50_c60_stdgradient	(32.5s	0.747007131	0.718607800	3.2690755134059932	0.539007092198
	processed_s80_c60_robustgradie	(1.1min	0.712202063	0.722414911	2.632459240848847	0.602069614299
	processed_s50_c60_stdgradient	(18.4s	0.572784004	0.707212100	0.4026479335557029	0.737588652482
	processed_s80_c60_robustgradie	(36.0s	0.525080042	0.718058551	-0.48170805264996774	0.785512699905
	> Group: xgboost 6	-		0.71181795	0.70121505	1.9909163028322625 (aver	0.52374129598
	> Group: catboost 6	-		0.68384492	0.69879140	1.5668875939094533 (aver	0.55663486964
	✓ ■ Group: random_forest 6	-		0.56014231	0.71745283	-0.45134163366474445 (av	0.69030913557
	processed_s50_c60_stdrandom_f	(5.3s	0.833418237	0.713818401	3.973265952267729	0.368794326241
30 matching re	uns						

Optimisation d'hyperparamètres

```
def compute custom_and_normalized(y_true: np.ndarray, y_pred_bin: np.ndarray,
                                  pos_proportion: float) -> Tuple[float, float]:
    """Compute custom and normalized scores based on confusion matrix."""
    tn, fp, fn, tp = confusion matrix(y true, y pred bin).ravel()
    custom = (2 * tp) + (1 * tn) - (1 * fp) - (10 * fn)
    n = len(y true)
    pos prop = max(pos proportion, 1e-9)
    normalized = custom * (1.0 / max(1, n)) * (1.0 / pos prop)
    return float(custom), float(normalized)
def find best threshold custom score(y true: np.ndarray, y pred proba: np.ndarray,
                                     pos proportion: float) -> Tuple float, float]:
    """Find the best threshold that maximizes the custom normalized score."""
    thresholds = np.linspace(0.01, 0.99, 99)
    best t, best score = 0.5, -np.inf
    for t in thresholds:
        y pred bin = (y pred proba >= t).astype(int)
        _, norm_score = _compute_custom_and_normalized(y_true, y_pred_bin, pos_proportion)
        if norm_score > best_score:
            best_score = norm_score
            best t = t
    return best_t, best_score
```

Y[target].mean()

Analyse modèle: pourquoi ça marche?



Soit +v la valeur que rapporte un prêt :

Sur 28 810 clients

+ 23 452 valeurs en prêts gagnants

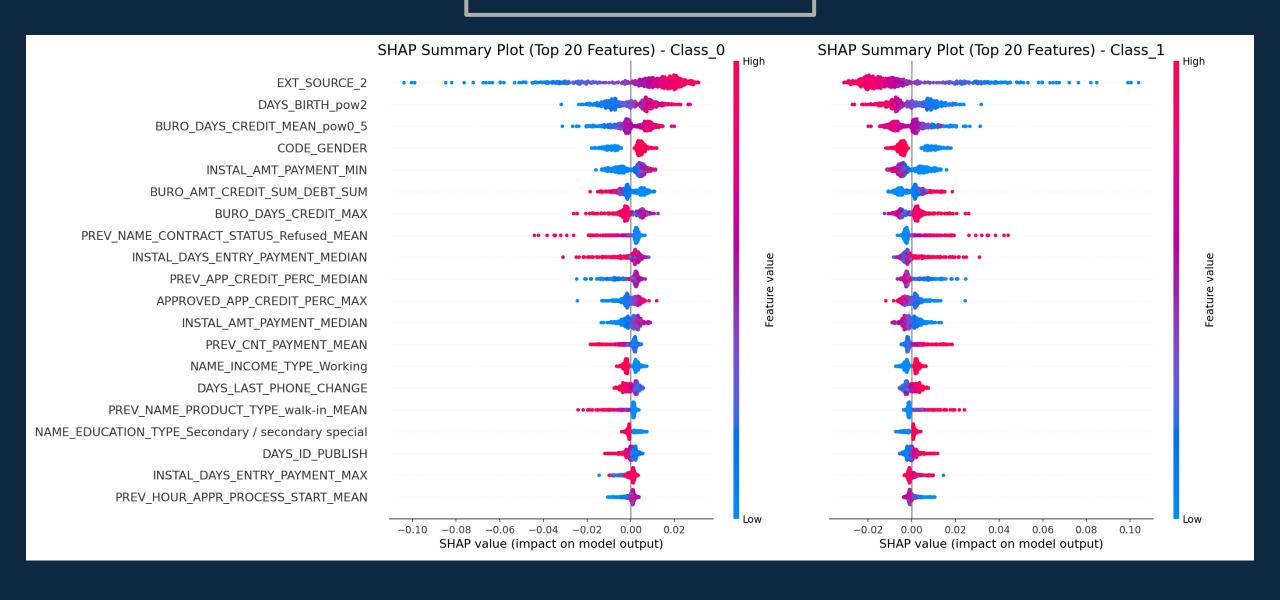
– 14 570 valeurs en prêts perdants

= 8882 valeurs de prêt

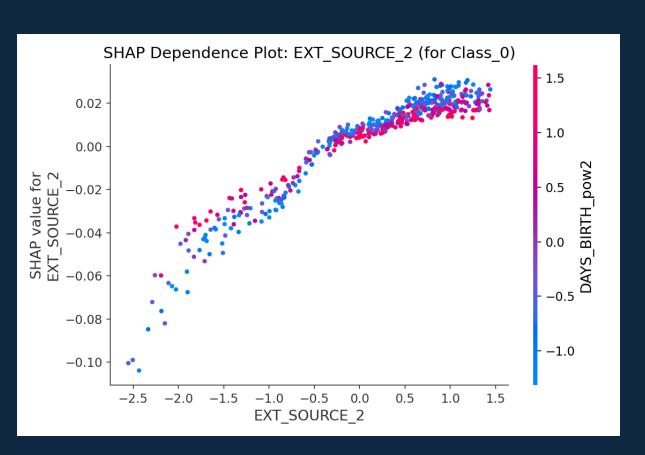
1 demande = 0.31 valeur

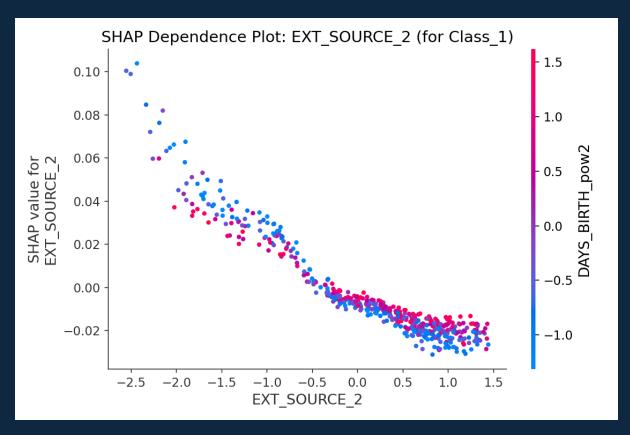
81.4% de prêt accordés

Analyse modèle

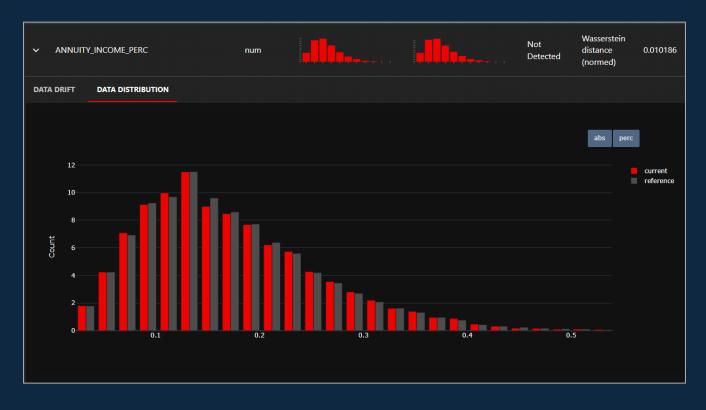


Analyse modèle





Dataset Drift Dataset Drift is NOT detected. Dataset drift detection threshold is 0.5							
43	0	0.0					
Columns	Drifted Columns	Share of Drifted Columns					

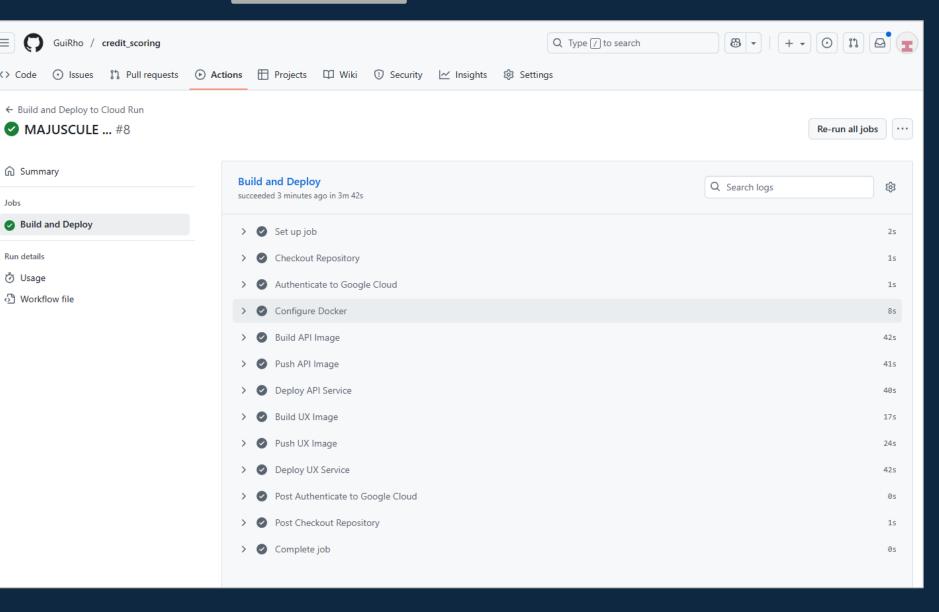








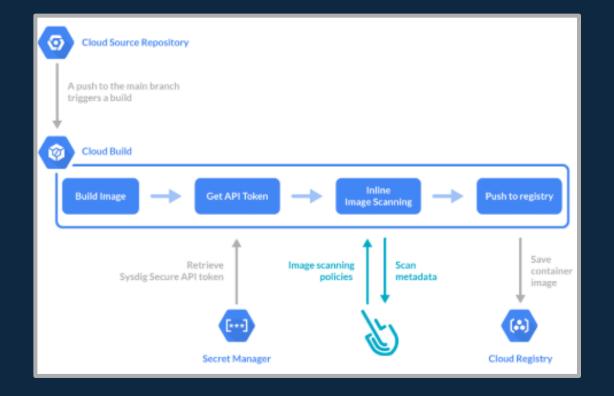
Jobs

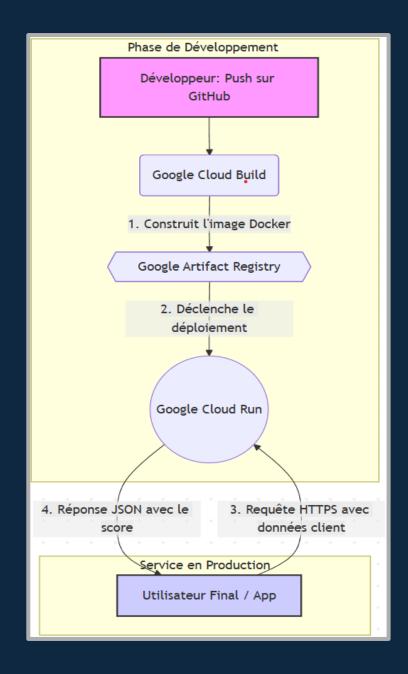


Google cloud









API: demo

URL: https://credit-scoring-ux-257261936398.europe-west1.run.app

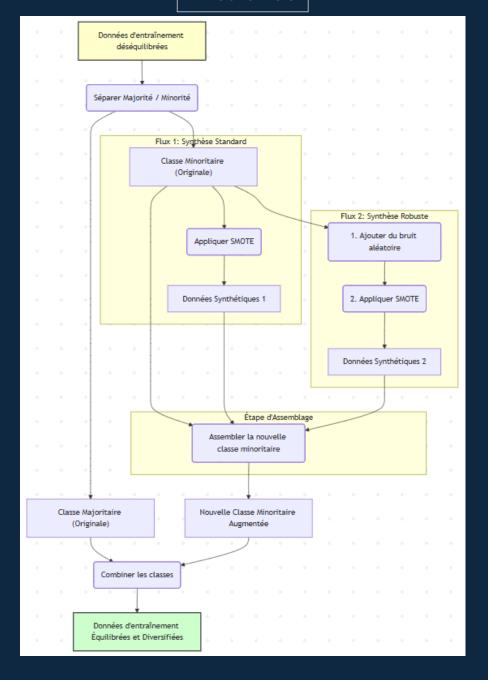
KNN

Données Brutes avec NAs Pour chaque colonne 'C' Calculer la Matrice de Corrélation 1. Consulter la matrice Identifier les 3 features les plus corrélées 2. Créer un sous-ensemble DataFrame Temporaire: [C, V1, V2, V3] 3. Appliquer l'algorithme KNN Imputer 4. Remplir les NAs de 'C' Mise à jour de 'C' Données Complètes et Imputées

Pour aller plus loin

- DL model
- Imputation KNN ciblée
- Algorithme de rééquilibrage hybride
- Stacking model : données à version

Imbalance



Stacking model

