Modèles basés sur des arbres en classifieurs faibles

Méthode de recalibrage utilisée ici : bordeline SMOTE (augmentation de la classe minoritaire à 50%). Paramètres : k=3 ; m=2.

(1) Importation des librairies

In [1]:
```
import os
import pandas as pd
import numpy as np
import dask.dataframe as dd
import matplotlib.pyplot as plt
import sys
import fastparquet
import dask_ml
from dask import delayed
from sklearn.metrics import *
import scikitplot as skplt
from dask_ml.preprocessing import StandardScaler
import pickle
```

(2) Import des algorithmes random forest, adaboost, Extrême Gradient Boosting

random forest : plusieurs arbres sont créés et chaque arbre est formé sur un échantillon du jeu d'entraînement avec bagging.

adaboost : avantages (1) simple d'utilisation (2) convergence de l'erreur d'entraînement / faible risque de sur-apprentissage. Principe : repose sur la sélection itérative du classifieur faible (un arbre) en fonction d'une distribution des exemples d'apprentissage. Chaque exemple est pondéré en fonction de sa difficulté avec le classifieur courant.

XGBoost(extreme gradient boosting) : Cette méthode repose sur les arbres de décision et s'améliore à partir d'autres méthodes telles que la forêt aléatoire. Elle est efficace avec les jeux de données volumineux et complexes en faisant appel à diverses méthodes d'optimisation.

In [2]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier

import dask
import dask
import xgboost
import dask_xgboost
```

```
C:\Users\chrys\anaconda3\lib\site-packages\dask_xgboost\__init__.py:7: UserWarning: Dask-XGBoost has been deprecated and is no lon
ger maintained. The functionality of this project has been included directly in XGBoost. To use Dask and XGBoost together, please
use ``xgboost.dask`` instead https://xgboost.readthedocs.io/en/latest/tutorials/dask.html. (https://xgboost.readthedocs.io/en/late
st/tutorials/dask.html.)
  warnings.warn(
```

In [3]:
```
#pip install dask.ml
```

In [4]:
```
#pip install scikit-plot
```

I. Préparation

(1) variables explicatives, variable à prédire et centrage-réduction

In [5]:
```
import os
os.chdir("C:/Fouille-donnees-massives")
```

In [6]:
```
# Dataframe d'apprentissage recalibré avec borderline SMOTE (k=3 ; k'=2)
df_train = dd.read_parquet("train_borderS")
df_train.info()
```

```
<class 'dask.dataframe.core.DataFrame'>
Columns: 12 entries, Montant to FlagImpaye
dtypes: float64(7), int64(5)
```

In [7]:
```
# Dataframe de test
df_test = dd.read_parquet("test_fast")
df_test.head()
```

Out[7]:

	FlagImpaye	Montant	VerifianceCPT1	D2CB	ScoringFP1	ScoringFP2	ScoringFP3	TauxImpNB_CPM	EcartNumCheq	NbrMagasin3J	DiffDateTr3	CA3TR
3899362	0	60.00	0	302	0.000000	0.000000	0.000000	52.076034	0	1	4.000000	0.00
3899363	0	25.00	0	547	0.000000	0.000000	0.000000	52.076034	0	1	4.000000	0.00
3899364	0	32.00	0	152	0.000000	0.000000	0.000000	52.076034	0	1	4.000000	0.00
3899365	0	20.88	0	393	0.007590	0.182221	0.002092	34.118277	4	1	1.539155	71.51
3899366	0	20.21	0	152	0.018994	-1.024399	0.005682	52.076034	0	1	4.000000	0.00

In [8]:
```
# Définir les variables explicatives et la variable cible
X_train = df_train.drop(["FlagImpaye"], axis = "columns")
X_test = df_test.drop(["FlagImpaye"], axis = "columns")

y_train = df_train["FlagImpaye"]
y_test = df_test["FlagImpaye"]
```

In [9]:
```
X_train.info()
```

```
<class 'dask.dataframe.core.DataFrame'>
Columns: 11 entries, Montant to CA3TR
dtypes: float64(7), int64(4)
```

In [10]:
```
# Instanciation de StandardScaler pour centrer-réduire les données
scaler = StandardScaler()
```

In [11]:
```
# Centrer-réduire le dataframe d'apprentissage
X_train = scaler.fit_transform(X_train)
X_train.head()
```

Out[11]:

	Montant	VerifianceCPT1	D2CB	ScoringFP1	ScoringFP2	ScoringFP3	TauxImpNB_CPM	EcartNumCheq	NbrMagasin3J	DiffDateTr3	CA3TR
0	-0.513979	-0.637594	1.268576	-0.118636	0.091466	-0.264064	0.629959	-0.047307	-0.191723	-0.430768	-0.187944
1	-0.513979	-0.637594	1.268576	-0.118636	0.091466	-0.264064	0.629959	-0.047302	4.691334	-0.430768	-0.094289
2	-0.169118	-0.637594	1.259694	-0.118636	0.091466	-0.264064	0.629959	-0.047307	-0.191723	-0.430768	-0.187944
3	-0.199811	1.157893	0.007401	-0.118636	0.091466	-0.264064	0.719130	-0.047307	-0.191723	-0.430768	-0.187944
4	-0.450761	-0.637594	1.259694	-0.118561	0.890092	-0.262793	0.629959	-0.047302	-0.191723	-0.430768	0.162853

In [12]:
```
# Centrer-réduire les dataframe de test
X_test = scaler.fit_transform(X_test)
X_test.head()
```

Out[12]:

	Montant	VerifianceCPT1	D2CB	ScoringFP1	ScoringFP2	ScoringFP3	TauxImpNB_CPM	EcartNumCheq	NbrMagasin3J	DiffDateTr3	CA3TR
3899362	-0.016999	0.0	0.265719	-0.080269	-0.043960	-0.317899	0.774799	-0.036921	-0.18432	-0.568544	-0.132257
3899363	-0.277531	0.0	1.427785	-0.080269	-0.043960	-0.317899	0.774799	-0.036921	-0.18432	-0.568544	-0.132257
3899364	-0.225425	0.0	-0.445750	-0.080269	-0.043960	-0.317899	0.774799	-0.036921	-0.18432	-0.568544	-0.132257
3899365	-0.308200	0.0	0.697344	-0.080074	-0.023966	-0.314458	-0.277090	-0.036897	-0.18432	-5.906429	1.259186
3899366	-0.313187	0.0	-0.445750	-0.079781	-0.156360	-0.308551	0.774799	-0.036921	-0.18432	-0.568544	-0.132257

(2) Maximisation de la marge

In [13]:
```
def perte(Montant):
    if Montant<=20:
        Montant=Montant*0
    elif 20<Montant<=50:
        Montant=0.2*Montant
    elif 50<Montant<=100:
        Montant=0.3*Montant
    elif 100<Montant<=200:
        Montant=0.5*Montant
    elif Montant>200:
        Montant=0.8*Montant
    return(Montant)
```

In [14]:
```
def Calcul_Marge(Montant, yReel, yPred):
    # Création de dfmerge
    dfmerge = pd.concat([Montant, yReel], axis=1)
    dfmerge["Ypred"] = yPred

    # Création de la variable Marge
    # Création d'une colonne Marge égale au Montant
    dfmerge["Marge"] = dfmerge["Montant"]
    #Calcul du gain ou de la perte selon la différence entre réel et prédiction
    dfmerge.loc[((dfmerge["FlagImpaye"] == 1) & (dfmerge["Ypred"] == 1)), "Marge"] = 0
    dfmerge.loc[((dfmerge["FlagImpaye"] == 0) & (dfmerge["Ypred"] == 1)), "Marge"] = 0.7 * 0.05 * dfmerge["Montant"]
    dfmerge.loc[((dfmerge["FlagImpaye"] == 1) & (dfmerge["Ypred"] == 0)), "Marge"] = dfmerge["Montant"].apply(lambda x: -perte(x))
    dfmerge.loc[((dfmerge["FlagImpaye"] == 0) & (dfmerge["Ypred"] == 0)), "Marge"] = 0.05 * dfmerge["Montant"]

    # Calcul du Marge_totale
    Marge_totale = dfmerge["Marge"].sum()

    return Marge_totale
```

(3) Modèles et performances

In [15]:
```
# Fonction de déploiement d'un modèle sur les données de test

# Création de la fonction de performance d'un modèle sur les données de test

def performances(modele, X_test, y_test, scale):

    X_test_ = X_test

    print("----------------------------------------------------------")


    if scale == True:
        X_test = scaler.transform(X_test) # scaler a été entrainé sur les données d'apprentissage

    # Affichage du modèle
    print('Modèle :\n', modele)
    print("----------------------------------------------------------")
    # Prédiction
    y_pred = delayed(modele.predict)(X_test).compute()
    # Prédiction des scores
    y_score = delayed(modele.predict_proba)(X_test).compute()

    # Estimateurs, matrice de confusion et AUC
    cm = delayed(confusion_matrix)(y_test, y_pred).compute()
    cr = delayed(classification_report)(y_test, y_pred).compute()
    auc = delayed(roc_auc_score)(y_test, y_pred).compute()
    f1 = delayed(f1_score)(y_test, y_pred).compute()

    print('F1_score :\n', f1)
    print("----------------------------------------------------------")
    print('Estimateurs :\n', cr)
    print("----------------------------------------------------------")
    print('Matrice de confusion :\n', cm)
    print("----------------------------------------------------------")
    print('Auc Score :\n', auc)
    print("----------------------------------------------------------")

    #Calcul de la Marge
    Marge_totale = Calcul_Marge(Montant = X_test_["Montant"].compute(), yReel = y_test.compute(), yPred = y_pred)
    print("Marge = " + str(round(Marge_totale, 2)) + " euros")

    print("----------------------------------------------------------")

    # Courbe ROC
    skplt.metrics.plot_roc(y_test, y_score, classes_to_plot = 1, plot_micro = False, plot_macro = False)
    # Courbe Précision-Rappel
    skplt.metrics.plot_precision_recall(y_test, y_score, classes_to_plot = 1, plot_micro = False)

    #return y_score,Marge_totale,auc,cr,cm
```

Si la courbe ROC tient la route avec un critère AUC élevé, cela signifie que l'apprentissage a bien fonctionné Si le F1_score est très mauvais, cela signifie alors que c'est le processus d'affectation qui n'a pas fonctionné.

III. Algorithmes

A. Random forest

GridSearch n'a pu être implémenté en raison des temps de traitement (tentative : pas de sortie au bout de 5h).

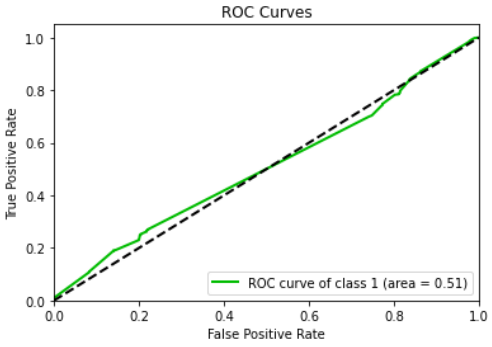
In [16]:
```
#Instanciation # 10 arbres #critère d'évaluation : indice de Gini (log_loss) # nb_mini_individus dans 1 feuille : 10
#Bootstrap = True (par défaut) #random_state= 0 déjà testé - 42 : le plus souvent utilisé avec "0"

RandomForest = RandomForestClassifier(n_estimators = 10, random_state = 0, min_samples_leaf = 10,min_samples_split=3)

# Fit your pipeline onto your training set (centré-réduit) and obtain predictions by fitting the model onto the test data
classifier1 = delayed(RandomForest.fit)(X_train, y_train)
```

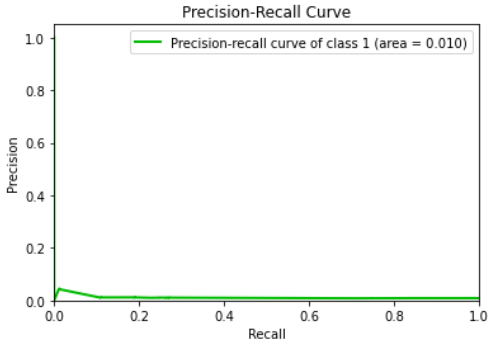
In [17]:
```
classifier1
```

Out[17]:
```
Delayed('fit-c7c388cf-7573-4c62-af32-0b8d8af777e6')
```

In [18]:
```
performances(classifier1, X_test, y_test,scale=True)
```

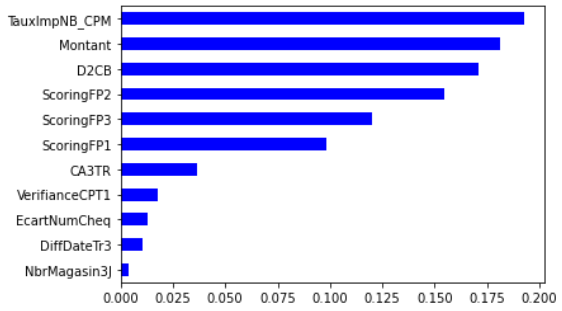
```
------------------------------------------------------------
Modèle :
 Delayed('fit-c7c388cf-7573-4c62-af32-0b8d8af777e6')
------------------------------------------------------------

C:\Users\chrys\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\chrys\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\chrys\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

F1_score :
 0.0
------------------------------------------------------------
Estimateurs :
              precision    recall  f1-score   support

           0       0.99      1.00      1.00    740837
           1       0.00      0.00      0.00      6573

    accuracy                           0.99    747410
   macro avg       0.50      0.50      0.50    747410
weighted avg       0.98      0.99      0.99    747410

------------------------------------------------------------
Matrice de confusion :
 [[740837      0]
 [  6573      0]]
------------------------------------------------------------
Auc Score :
 0.5
------------------------------------------------------------
Marge = -98.31 euros
------------------------------------------------------------
```





In [19]:
```
#dir(RandomForest)
```

In [20]:
```
importances = pd.Series(RandomForest.feature_importances_, index = X_test.columns)
sorted_importances = importances.sort_values()
sorted_importances.plot(kind='barh', color='blue')
plt.show()
```



****Tuning -: (1) Le modèle n'est pas très bon (marge) = -98.31€ (2) on mise sur le bagging pour réduire l'instabilité****

In [21]:
```
from sklearn.ensemble import BaggingClassifier
#from sklearn.model_selection import GridSearchCV # annulé pour cause de durée de traitement
```

In [37]:
```
#avec bagging
model_best= RandomForestClassifier(n_estimators = 10, random_state = 0, min_samples_leaf = 10,min_samples_split=3)

modele_best =BaggingClassifier(base_estimator=model_best,n_estimators = 1, random_state = 0,n_jobs=-1)
```

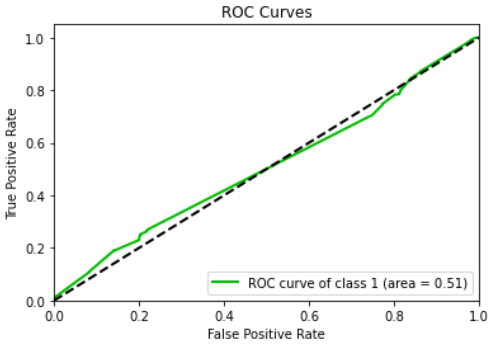
In [38]:
```
# Fit your pipeline onto your training set and obtain predictions by fitting the model onto the test data
classifierb = delayed(model_best.fit)(X_train, y_train).compute()
```

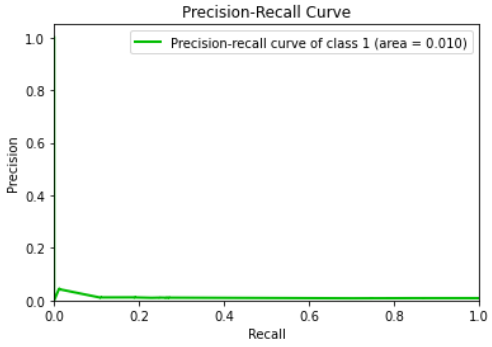
In [39]:
```
classifierb
```

Out[39]:
```
RandomForestClassifier(min_samples_leaf=10, min_samples_split=3,
                       n_estimators=10, random_state=0)
```

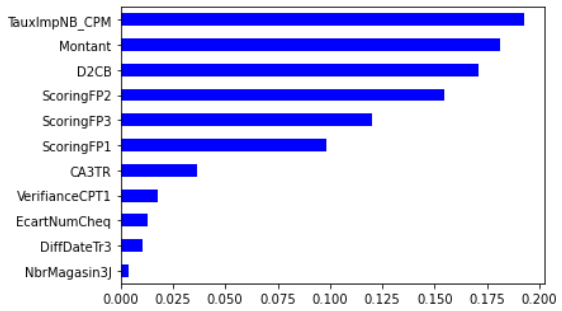
In [40]:
```
performances(classifierb, X_test, y_test,scale=True)
```

```
------------------------------------------------------
Modèle :
 RandomForestClassifier(min_samples_leaf=10, min_samples_split=3,
                        n_estimators=10, random_state=0)
------------------------------------------------------

C:\Users\chrys\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\chrys\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\chrys\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

F1_score :
 0.0
------------------------------------------------------
Estimateurs :
              precision    recall  f1-score   support

           0       0.99      1.00      1.00    740837
           1       0.00      0.00      0.00      6573

    accuracy                           0.99    747410
   macro avg       0.50      0.50      0.50    747410
weighted avg       0.98      0.99      0.99    747410

------------------------------------------------------
Matrice de confusion :
 [[740837      0]
 [  6573      0]]
------------------------------------------------------
Auc Score :
 0.5
------------------------------------------------------
Marge = -98.31 euros
------------------------------------------------------
```





In [42]:
```
importances = pd.Series(model_best.feature_importances_, index = X_test.columns)
sorted_importances = importances.sort_values()
sorted_importances.plot(kind='barh', color='blue')
plt.show()
```



B. Adaboost

Comme supposé, le modèle est meilleur (marge positive par exemple, précision de 10%, ...).

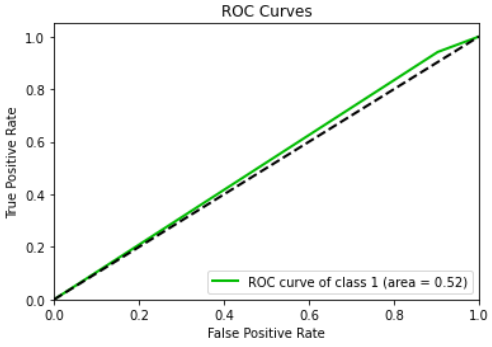
In [29]:
```
# Instanciation avec les mêmes paramètres
dtree = DecisionTreeClassifier(n_estimators = 10, random_state = 0, min_samples_leaf = 10,min_samples_split=3, max_depth = 2)

AdaBoost = AdaBoostClassifier(base_estimator = dtree, random_state = 0, n_estimators = 1)

# Fit your pipeline onto your training set and obtain predictions by fitting the model onto the test data
classifier4 = delayed(AdaBoost.fit)(X_train, y_train).compute()
```

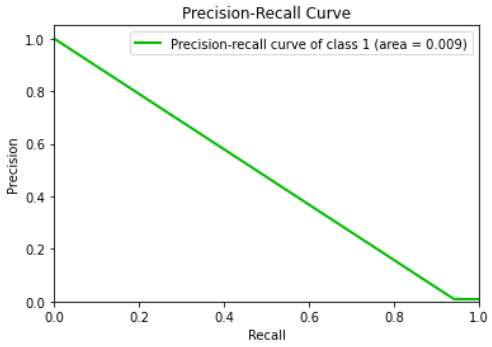
In [30]:
```
classifier4
```

Out[30]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=1,
                                                         random_state=0),
                   n_estimators=1, random_state=0)
```

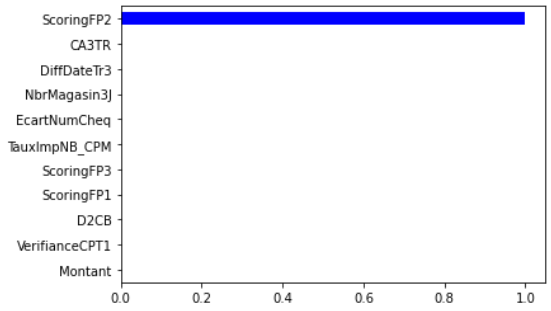
In [31]:
```
performances(classifier4, X_test, y_test,scale=True)
```

```
----------------------------------------------------------
Modèle :
 AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=1,
                                                         random_state=0),
                   n_estimators=1, random_state=0)
----------------------------------------------------------
F1_score :
 0.01815151497367942
----------------------------------------------------------
Estimateurs :
              precision    recall  f1-score   support

           0       0.99      0.10      0.18    740837
           1       0.01      0.94      0.02      6573

    accuracy                           0.10    747410
   macro avg       0.50      0.52      0.10    747410
weighted avg       0.99      0.10      0.18    747410

----------------------------------------------------------
Matrice de confusion :
 [[ 72000 668837]
 [   387   6186]]
----------------------------------------------------------
Auc Score :
 0.5191550727448966
----------------------------------------------------------
Marge = 155.67 euros
----------------------------------------------------------
```





In [45]:
```
importances = pd.Series(AdaBoost.feature_importances_, index = X_test.columns)
sorted_importances = importances.sort_values()
sorted_importances.plot(kind='barh', color='blue')
plt.show()
```



C. XGradient boosting

XGBoost paraît etre le meilleur modèle de cette famille, parmi les 3 testés. Un arbre tout simple, peu profond, suffit à générer en tendance les meilleurs résultats.

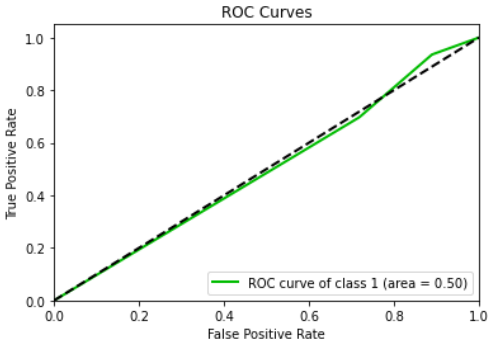
In [46]:
```
# En pratique, ces arbres sont peu profonds, nous conservons max_depth=2

from xgboost import XGBClassifier

dtree = DecisionTreeClassifier(max_depth = 2, random_state = 0)

modele = XGBClassifier(base_estimator = dtree, n_estimators = 1, random_state = 0)
# Fit your pipeline onto your training set and obtain predictions by fitting the model onto the test data
classifier5 = delayed(modele.fit)(X_train, y_train).compute()
```

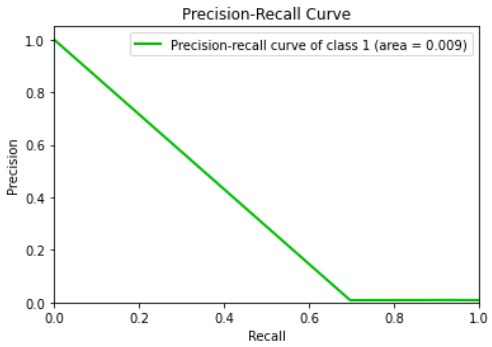
In [48]:
```
classifier5
```

Out[48]:
```
XGBClassifier(base_estimator=DecisionTreeClassifier(max_depth=2,
                                                    random_state=0),
              n_estimators=1)
```

In [49]:
```
performances(classifier5, X_test, y_test,scale=True)
```

```
------------------------------------------------------------
Modèle :
 XGBClassifier(base_estimator=DecisionTreeClassifier(max_depth=2,
                                                     random_state=0),
              n_estimators=1)
------------------------------------------------------------
F1_score :
 0.018304870674375865
------------------------------------------------------------
Estimateurs :
               precision    recall  f1-score   support

           0       0.99      0.11      0.20    740837
           1       0.01      0.93      0.02      6573

    accuracy                           0.12    747410
   macro avg       0.50      0.52      0.11    747410
weighted avg       0.99      0.12      0.20    747410

------------------------------------------------------------
Matrice de confusion :
 [[ 82149 658688]
 [   428   6145]]
------------------------------------------------------------
Auc Score :
 0.5228859382155968
------------------------------------------------------------
Marge = 166.64 euros
------------------------------------------------------------
```





In [50]:
```
importances = pd.Series(modele.feature_importances_, index = X_test.columns)
sorted_importances = importances.sort_values()
sorted_importances.plot(kind='barh', color='blue')
plt.show()
```