In [1]:

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from IPython.display import display
from collections import Counter
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report,roc_curve, roc_auc_sc
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
import scikitplot as skplt
from IPython.display import display
#from pycaret .classification import *
```

In [2]:

```
dtypes = {  'Regiao': 'object',
            'UF': 'object',
            'CNAE': 'object',
            'Atendida':'bool',
            'CodAssunto': 'object',
            'SexoConsumidor': 'object',
            'FaixaEtaria': 'object',
            'CEP': 'object',
            'InscritoDAU':'bool'}
```

In [3]:

```
df_ml1 = pd.read_csv(r'C:\Users\73594253368\Desktop\Curso\Datasets\Procon\dataset_trata
```

In [4]:

```
df_ml1 = df_ml1[['Regiao','UF','CNAE','Atendida','CodAssunto','SexoConsumidor','FaixaEt
```

In [5]:

```
# Este df_ml1 foi a primeira tentativa. Manteremos esse data frame para testes demonstr
# Para o ML "oficial", copiaremos esse df_ml1 para o df_ml
df_ml = df_ml1
```

In [6]:

```
df_ml
```

Out[6]:

	Regiao	UF	CNAE	Atendida	CodAssunto	SexoConsumidor	FaixaEtaria	CE
0	Norte	RO	6120501.0	False	187.0	M	5	76824042
1	Norte	RO	3514000.0	False	185.0	M	4	76824322
2	Norte	RO	8599604.0	True	236.0	M	3	78932000
3	Norte	RO	6120501.0	True	187.0	M	5	78932000
4	Norte	RO	6493000.0	False	57.0	M	6	76821331
...	...	...	...	...	...	...	...	
10514	Sudeste	SP	6110801.0	True	187.0	F	4	9617000
10515	Norte	RO	6143400.0	True	259.0	M	2	76940000
10516	Norte	RO	6422100.0	False	63.0	F	6	76990000
10517	Norte	RO	3514000.0	False	185.0	F	4	76807400
10518	Norte	RO	6423900.0	True	53.0	F	3	76806420

10519 rows × 9 columns

In [7]:

```
# Demonstração do desbalanceamento na variável "target"
df_ml['Atendida'].value_counts()
```

Out[7]:

```
True     6306
False    4213
Name: Atendida, dtype: int64
```

Aplicando SMOTE

Data Preparation

As variáveis preditoras mais importantes do nosso dataset são as categóricas. Assim, como etapa preparatória do SMOTE, temos que criar variáveis dummies. Testamos, antes, com SMOTE e sem dummies e, também, o tradicional dummies sem SMOTE. Igualmente testamos LabelEncoder + dummies + SMOTE. Os melhores resultados de acurária e recall foram com o procedimento a seguir.

In [8]:

```
df_ml.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10519 entries, 0 to 10518
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Regiao          10519 non-null  object
 1   UF              10519 non-null  object
 2   CNAE            10519 non-null  object
 3   Atendida        10519 non-null  bool  
 4   CodAssunto      10519 non-null  object
 5   SexoConsumidor  10519 non-null  object
 6   FaixaEtaria     10519 non-null  object
 7   CEP             10519 non-null  object
 8   InscritoDAU     10519 non-null  bool  
dtypes: bool(2), object(7)
memory usage: 595.9+ KB
```

In [9]:

```
df_ml = pd.get_dummies(df_ml[['Regiao',
                              'UF',
                              'CNAE',
                              'Atendida',
                              'CodAssunto',
                              'SexoConsumidor',
                              'FaixaEtaria',
                              'CEP','InscritoDAU']])
```

In [10]:

```
df_ml.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10519 entries, 0 to 10518
Columns: 6928 entries, Atendida to CEP_9990244.0
dtypes: bool(2), uint8(6926)
memory usage: 69.5 MB
```

In [11]:

```
df_ml.shape
```

Out[11]:

```
(10519, 6928)
```

SMOTE após dummies

In [12]:

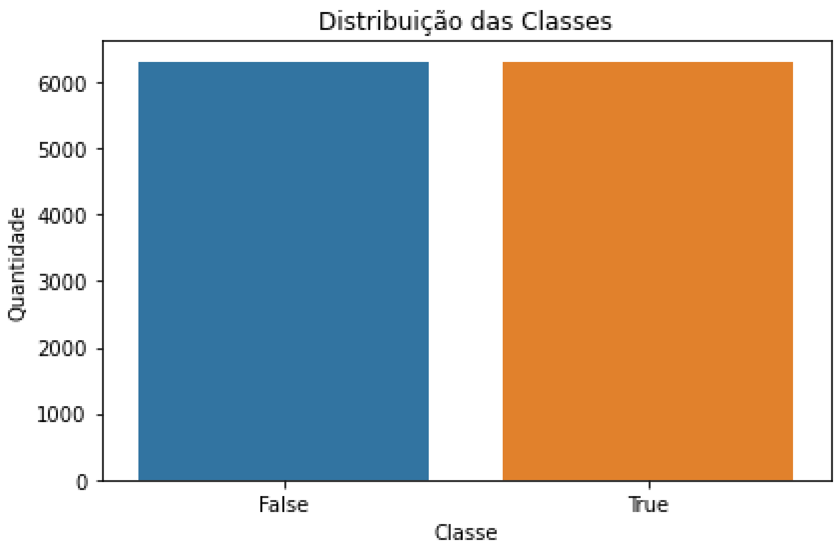
```
X = df_ml.drop(['Atendida'],axis=1)
y = df_ml.Atendida
smt = SMOTE()
X_os,y_os = smt.fit_sample(X,y) #os de oversampled
counter = Counter(y_os)
print(counter)
```

```
Counter({False: 6306, True: 6306})
```

In [13]:

```
#grafico da nova distribuição de classes
fig, ax = plt.subplots()
sns.countplot(y_os, ax=ax)
ax.set_title('Distribuição das Classes')
plt.xlabel('Classe')
plt.ylabel('Quantidade')
plt.tight_layout();

#print do balanceamento
print(pd.Series(y_os).value_counts())
```

```
D:\ANACONDA\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(

True     6306
False    6306
Name: Atendida, dtype: int64
```



In [14]:

```
#Train_test_split nessa oversampled
#Especificamos o tamanho do test_size = 0.3 pq assim as True/False do ytreinamento e as
xtreinamento, xteste, ytreinamento, yteste = train_test_split(X_os, y_os, test_size = 0
```

In [15]:

```
1 xtreinamento
```

Out[15]:

	InscritoDAU	Regiao_Centro-oeste	Regiao_Nordeste	Regiao_Norte	Regiao_Sudeste	Regiao_S
11454	False	1	0	0	0	
8765	False	0	0	0	1	
3191	False	0	0	0	1	
2792	False	0	0	0	1	
9375	True	0	0	0	1	
...	...	...	...	...	...	
12177	True	0	1	0	0	
8964	True	0	0	0	1	
4682	False	0	0	0	1	
5278	False	1	0	0	0	
7598	False	0	0	0	1	

8828 rows × 6927 columns

In [16]:

```
1 xteste
```

Out[16]:

	InscritoDAU	Regiao_Centro-oeste	Regiao_Nordeste	Regiao_Norte	Regiao_Sudeste	Regiao_Su
6594	False	0	0	0	0	
6068	False	0	0	0	1	
3782	False	0	0	1	0	
1772	False	0	0	0	0	
289	False	0	0	0	1	
...	...	...	...	...	...	
9219	True	0	0	1	0	
43	False	0	0	0	1	
4719	False	0	0	0	1	
225	False	0	0	0	1	
9295	False	0	1	0	0	

3784 rows × 6927 columns

In [17]:

```
ytreinamento.value_counts()
```

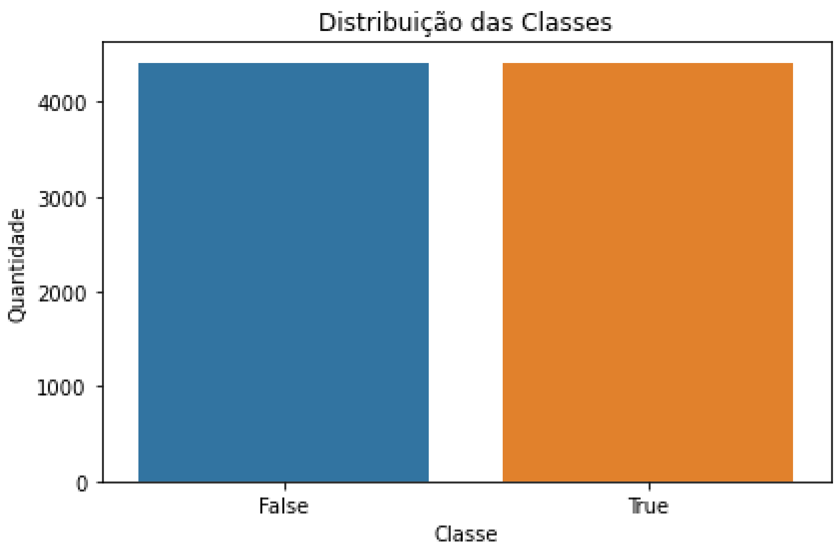
Out[17]:

```
True     4414
False    4414
Name: Atendida, dtype: int64
```

In [18]:

```
fig, ax = plt.subplots()
sns.countplot(ytreinamento, ax=ax)
ax.set_title('Distribuição das Classes')
plt.xlabel('Classe')
plt.ylabel('Quantidade')
plt.tight_layout();

#print do balanceamento
print(pd.Series(ytreinamento).value_counts())
```

```
True     4414
False    4414
Name: Atendida, dtype: int64

D:\ANACONDA\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [19]:

```
yteste.value_counts()
```

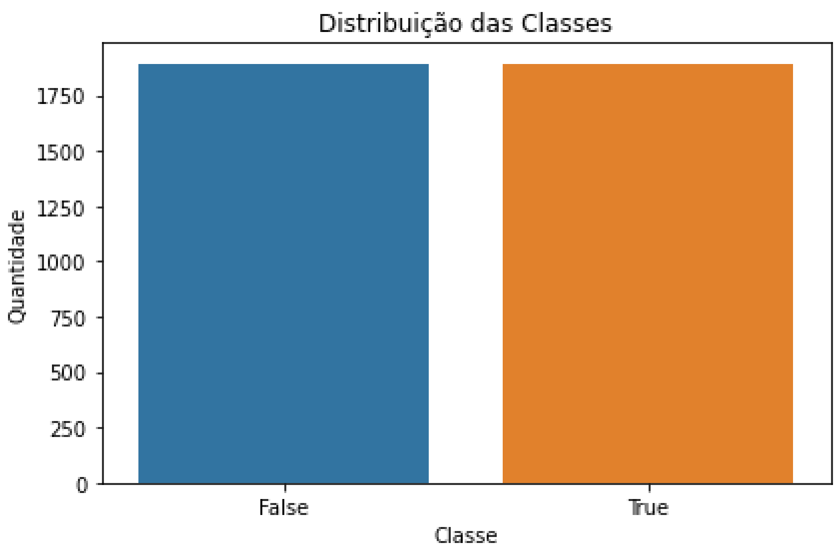
Out[19]:

```
True     1892
False    1892
Name: Atendida, dtype: int64
```

In [20]:

```
fig, ax = plt.subplots()
sns.countplot(yteste, ax=ax)
ax.set_title('Distribuição das Classes')
plt.xlabel('Classe')
plt.ylabel('Quantidade')
plt.tight_layout();

#print do balanceamento
print(pd.Series(ytreinamento).value_counts())
```

```
D:\ANACONDA\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(

True     4414
False    4414
Name: Atendida, dtype: int64
```



In [21]:

```
#Neste ponto do notebook, as bases do "df_ml" estão balanceadas pelo SMOTE e separadas
```

PyCaret preparatório

Temos as bases balanceadas e já separadas no train_test_split. Todavia, não sabemos qual modelo de machine learning aplicar. Utilizaremos a ferramenta de automação de machine learning Pycaret apenas como guia para escolher os melhores algoritmos para implementação manual.

A documentação do PyCaret dispõe que, ao utilizar o parâmetro fix_imbalance=True, a biblioteca aplica, automaticamente, a técnica SMOTE. Dessa forma, não há necessidade de aplicar as bases balanceadas por SMOTE, às quais preparamos para o ML manual. Assim, utilizaremos, no PyCaret, a base "df_ml1". Como haverá SMOTE automático, a ml1 será semelhante à "df_ml" submetida ao SMOTE

In [22]:

```
#PyCaret no automático mas com fix_imbalance=True
#pycaret_df_ml = setup(data = ml1, target='Atendida',fix_imbalance=True)
#modelsml1 = compare_models()
#resultsml1 = pull()
```

#Resultado do PyCaret:

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
ridge	Ridge Classifier	0.7333	0.0000	0.7642	0.7873	0.7754	0.4471	0.4477	16.6980
et	Extra Trees Classifier	0.7308	0.7868	0.7998	0.7648	0.7816	0.4311	0.4325	33.3220
rf	Random Forest Classifier	0.7291	0.7867	0.8129	0.7560	0.7833	0.4231	0.4253	23.5580
lr	Logistic Regression	0.7250	0.7892	0.7380	0.7918	0.7638	0.4355	0.4374	31.5750
svm	SVM - Linear Kernel	0.7229	0.0000	0.7315	0.7974	0.7593	0.4327	0.4393	16.7670
dt	Decision Tree Classifier	0.7206	0.7016	0.7967	0.7538	0.7745	0.4081	0.4094	15.5360
lightgbm	Light Gradient Boosting Machine	0.7201	0.7718	0.7649	0.7696	0.7671	0.4163	0.4166	16.7510
gbc	Gradient Boosting Classifier	0.7027	0.7645	0.7344	0.7637	0.7486	0.3852	0.3859	27.2430
ada	Ada Boost Classifier	0.6925	0.7554	0.7000	0.7692	0.7327	0.3726	0.3752	17.9490
knn	K Neighbors Classifier	0.6345	0.7270	0.5246	0.7999	0.6333	0.2993	0.3262	32.0240
nb	Naive Bayes	0.5263	0.5962	0.2563	0.8570	0.3943	0.1625	0.2440	14.8830
lda	Linear Discriminant Analysis	0.4105	0.4492	0.4043	0.4638	0.4320	0.2171	0.2199	181.5890
qda	Quadratic Discriminant Analysis	0.3917	0.4549	0.1470	0.6861	0.2419	0.0912	0.1603	110.5300

ML manual a partir dos melhores modelos que prospectamos com o PyCaret: et, rf e lr. Privilegiando o recall e, também, para variar dos modelos de árvore, colocamos, também, o lightgbm. Plotamos Matriz de Confusão e grafico de ROC e AUC.

In [23]:

```
#Retomamos os train_test_split a partir do oversample ("_os") que já tínhamos feito
```

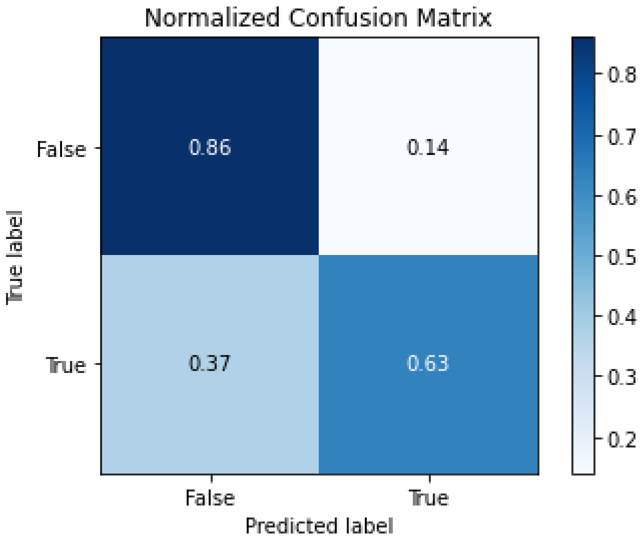
In [29]:

```
# Modelo Extra Trees Classifier
et = ExtraTreesClassifier(random_state=0)
et = et.fit(xtreinamento, ytreinamento)
Train_predict_et = et.predict(xteste)
print("Accuracy Score:", accuracy_score(yteste, Train_predict_et))
print(classification_report(yteste, Train_predict_et))
```

```
Accuracy Score: 0.7457716701902748
              precision    recall  f1-score   support

       False       0.70      0.86      0.77      1892
        True       0.82      0.63      0.71      1892

    accuracy                           0.75      3784
   macro avg       0.76      0.75      0.74      3784
weighted avg       0.76      0.75      0.74      3784
```

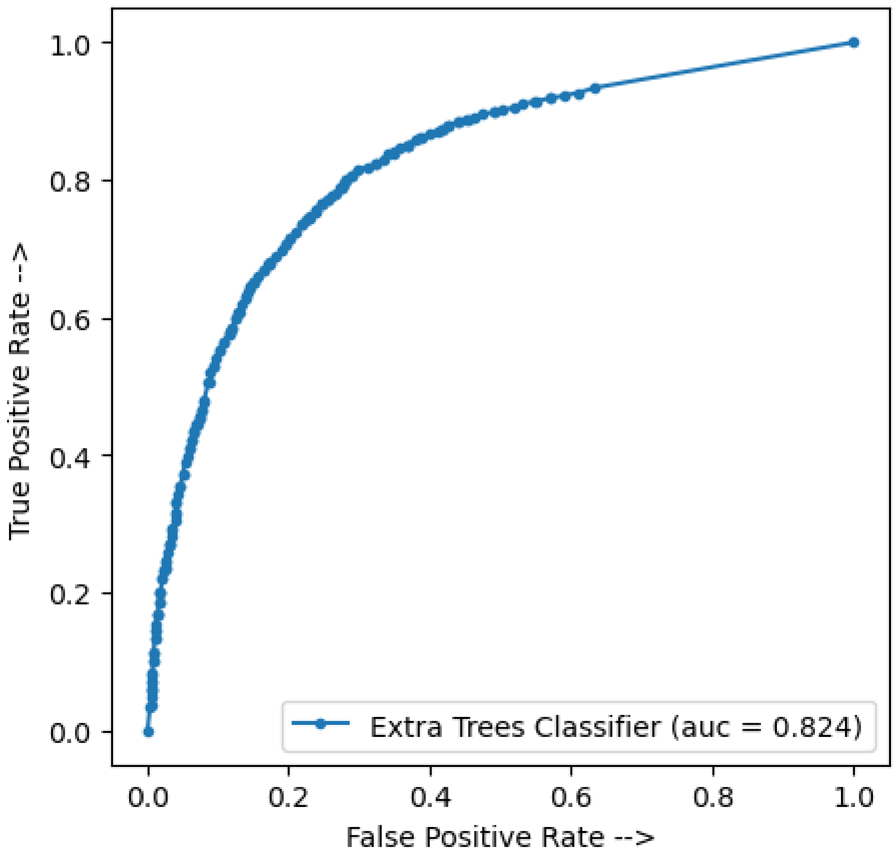
In [30]:

```
#Matriz de Confusão
skplt.metrics.plot_confusion_matrix(yteste, Train_predict_et, normalize=True)
plt.show()
```



In [31]:

```
# Curva ROC e área abaixo da curva (AUC)
y_pred_et = et.predict_proba(xteste)
et_fpr,et_tpr,thereshold = roc_curve(yteste,y_pred_et[:,1])
auc_et = auc(et_fpr,et_tpr)
plt.figure(figsize=(5, 5), dpi=100)
plt.plot(et_fpr,et_tpr, marker='.', label='Extra Trees Classifier (auc = %0.3f)' % auc_
plt.xlabel('False Positive Rate -->')
plt.ylabel('True Positive Rate -->')
plt.legend()
plt.show()
```



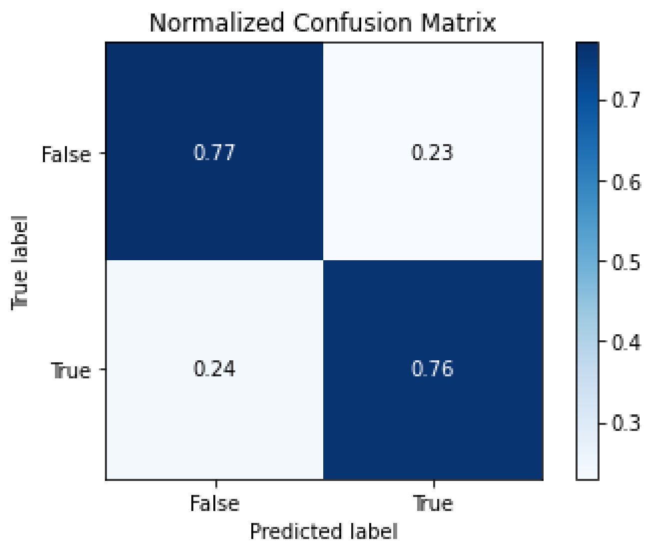
In [32]:

```
# Modelo Logistic Regression
lr = LogisticRegression(random_state=0)
lr = lr.fit(xtreinamento, ytreinamento)
Train_predict_lr = lr.predict(xteste)
print("Accuracy Score:", accuracy_score(yteste, Train_predict_lr))
print(classification_report(yteste, Train_predict_lr))
```

```
D:\ANACONDA\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converg
enceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(

Accuracy Score: 0.7618921775898521
              precision    recall  f1-score   support

       False       0.76      0.77      0.76      1892
        True       0.76      0.76      0.76      1892

    accuracy                           0.76      3784
   macro avg       0.76      0.76      0.76      3784
weighted avg       0.76      0.76      0.76      3784
```

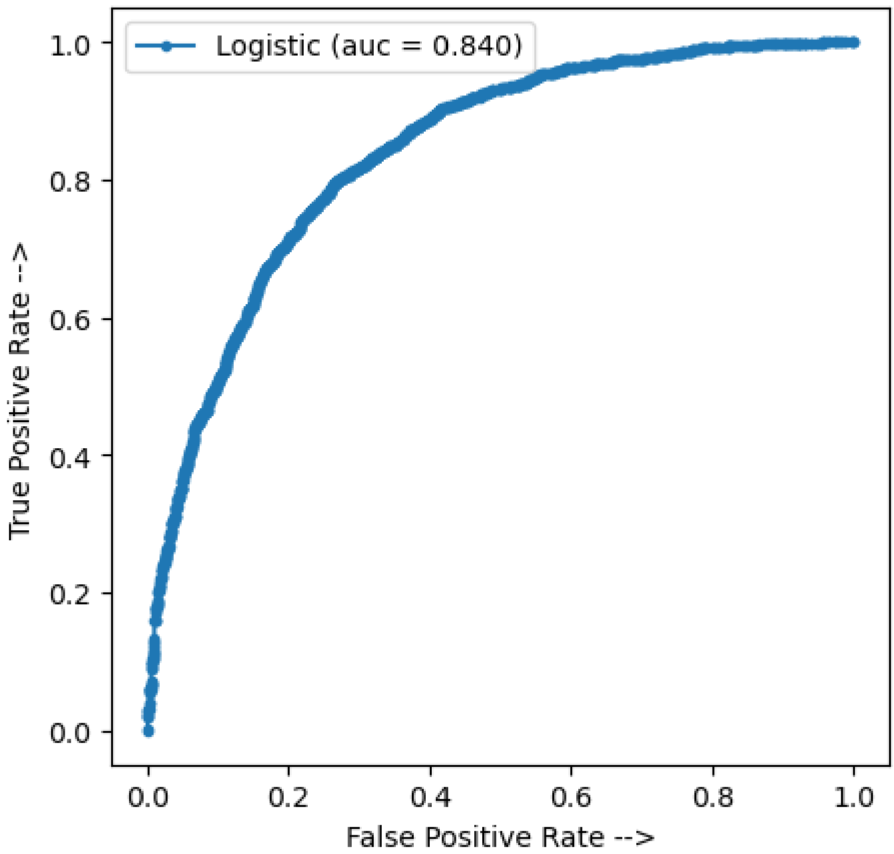
In [33]:

```
skplt.metrics.plot_confusion_matrix(yteste, Train_predict_lr, normalize=True)
plt.show()
```



In [34]:

```
Y_pred_lr=lr.decision_function(xteste)
logistic_fpr,logistic_tpr,thereshold = roc_curve(yteste,Y_pred_lr) # Y_pred_lr do decis
auc_logistic = auc(logistic_fpr, logistic_tpr)
plt.figure(figsize=(5, 5), dpi=100)
plt.plot(logistic_fpr, logistic_tpr, marker='.', label='Logistic (auc = %0.3f)' % auc_l
plt.xlabel('False Positive Rate -->')
plt.ylabel('True Positive Rate -->')
plt.legend()
plt.show()
```



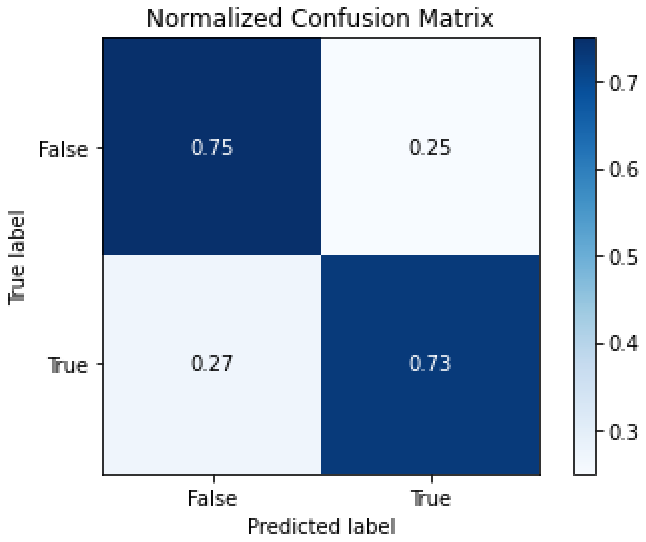
In [35]:

```
# Modelo Light Gradient Boosting Machine
import lightgbm
from lightgbm import LGBMClassifier
lightgbm = LGBMClassifier(random_state=0)
lightgbm = lightgbm.fit(xtreinamento, ytreinamento)
Train_predict_lightgbm = lightgbm.predict(xteste)
print("Accuracy Score:", accuracy_score(yteste, Train_predict_lightgbm))
print(classification_report(yteste, Train_predict_lightgbm))
```

```
Accuracy Score: 0.7418076109936576
              precision    recall  f1-score   support

       False       0.74      0.75      0.74      1892
        True       0.75      0.73      0.74      1892

    accuracy                           0.74      3784
   macro avg       0.74      0.74      0.74      3784
weighted avg       0.74      0.74      0.74      3784
```

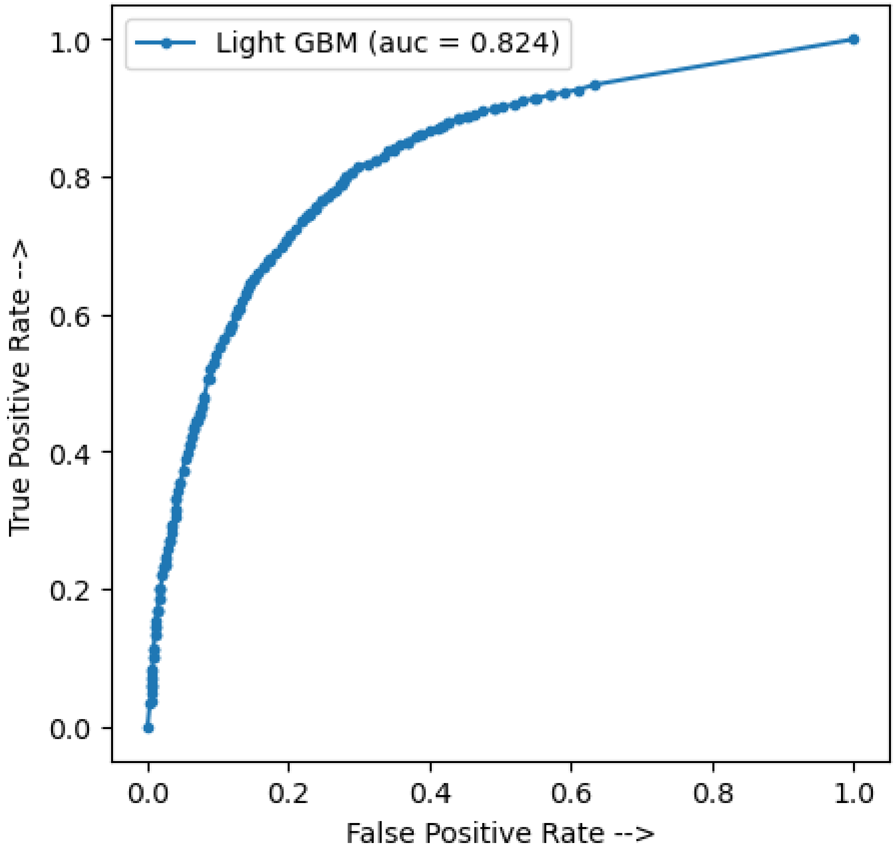
In [36]:

```
skplt.metrics.plot_confusion_matrix(yteste, Train_predict_lightgbm, normalize=True)
plt.show()
```



In [37]:

```
y_pred_lightgbm = lightgbm.predict_proba(xteste)
lightgbm_fpr,lightgbm_tpr,thereshold = roc_curve(yteste,y_pred_et[:,1])
auc_lightgbm = auc(lightgbm_fpr,lightgbm_tpr)
plt.figure(figsize=(5, 5), dpi=100)
plt.plot(lightgbm_fpr,lightgbm_tpr, marker='.', label='Light GBM (auc = %0.3f)' % auc_l
plt.xlabel('False Positive Rate -->')
plt.ylabel('True Positive Rate -->')
plt.legend()
plt.show()
```



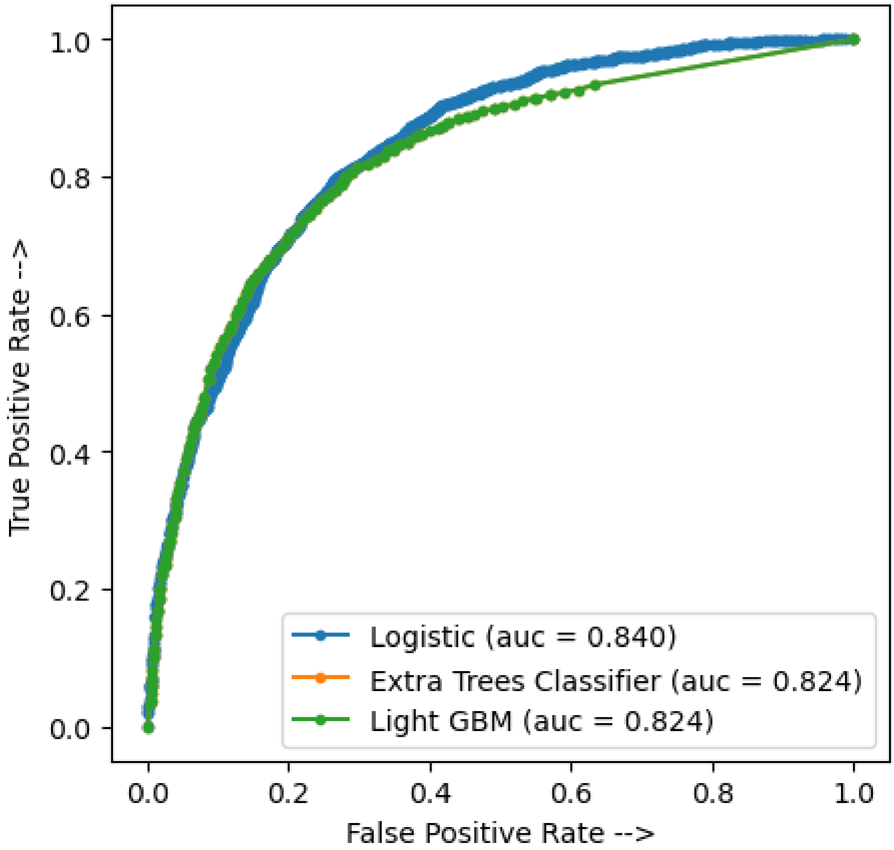
In [43]:

```python
# Comparativo dos três modelos
print("EXTRA TREES CLASSIFIER:")
print("Accuracy Score:", accuracy_score(yteste, Train_predict_et))
print(classification_report(yteste, Train_predict_et))
print("REGRESSÃO LOGÍSTICA:")
print("Accuracy Score:", accuracy_score(yteste, Train_predict_lr))
print(classification_report(yteste, Train_predict_lr))
print("LIGHTGBM:")
print("Accuracy Score:", accuracy_score(yteste, Train_predict_lightgbm))
print(classification_report(yteste, Train_predict_lightgbm))
```

```
EXTRA TREES CLASSIFIER:
Accuracy Score: 0.7457716701902748
              precision    recall  f1-score   support

       False       0.70      0.86      0.77      1892
        True       0.82      0.63      0.71      1892

    accuracy                           0.75      3784
   macro avg       0.76      0.75      0.74      3784
weighted avg       0.76      0.75      0.74      3784

REGRESSÃO LOGÍSTICA:
Accuracy Score: 0.7618921775898521
              precision    recall  f1-score   support

       False       0.76      0.77      0.76      1892
        True       0.76      0.76      0.76      1892

    accuracy                           0.76      3784
   macro avg       0.76      0.76      0.76      3784
weighted avg       0.76      0.76      0.76      3784

LIGHTGBM:
Accuracy Score: 0.7418076109936576
              precision    recall  f1-score   support

       False       0.74      0.75      0.74      1892
        True       0.75      0.73      0.74      1892

    accuracy                           0.74      3784
   macro avg       0.74      0.74      0.74      3784
weighted avg       0.74      0.74      0.74      3784
```

In [44]:

```
# Comparando AUC dos modelos ExtraTrees, LogisticRegression e LightGBM
plt.figure(figsize=(5, 5), dpi=100)
plt.plot(logistic_fpr, logistic_tpr, marker='.', label='Logistic (auc = %0.3f)' % auc_l
plt.plot(et_fpr,et_tpr, marker='.', label='Extra Trees Classifier (auc = %0.3f)' % auc_
plt.plot(lightgbm_fpr,lightgbm_tpr, marker='.', label='Light GBM (auc = %0.3f)' % auc_l
plt.xlabel('False Positive Rate -->')
plt.ylabel('True Positive Rate -->')
plt.legend()
plt.show()
```



A exigência da PUC Minas é de, no mínimo, três modelos de ML. Conforme demonstramos abaixo, o RandomForest gera basicamente o mesmo resultado do ExtraTrees. Dessa forma, utilizaremos, na versão a ser apresentada, os modelos ExtraTrees, LogisticRegression e LightGBM.

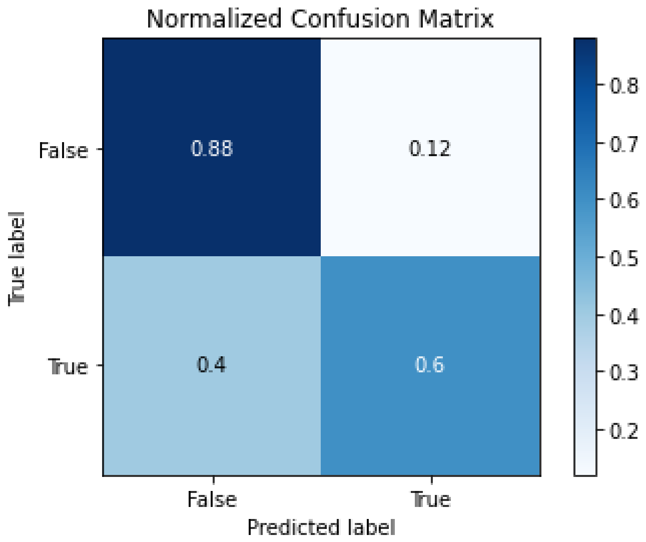
In [40]:

```
#Modelo RandomForest
rfm = RandomForestClassifier()
rfm = rfm.fit(xtreinamento, ytreinamento)
tp_rfm = rfm.predict(xteste)
print("Accuracy Score:", accuracy_score(yteste, tp_rfm))
print(classification_report(yteste, tp_rfm))
```

```
Accuracy Score: 0.7370507399577167
              precision    recall  f1-score   support

       False       0.69      0.88      0.77      1892
        True       0.83      0.60      0.69      1892

    accuracy                           0.74      3784
   macro avg       0.76      0.74      0.73      3784
weighted avg       0.76      0.74      0.73      3784
```

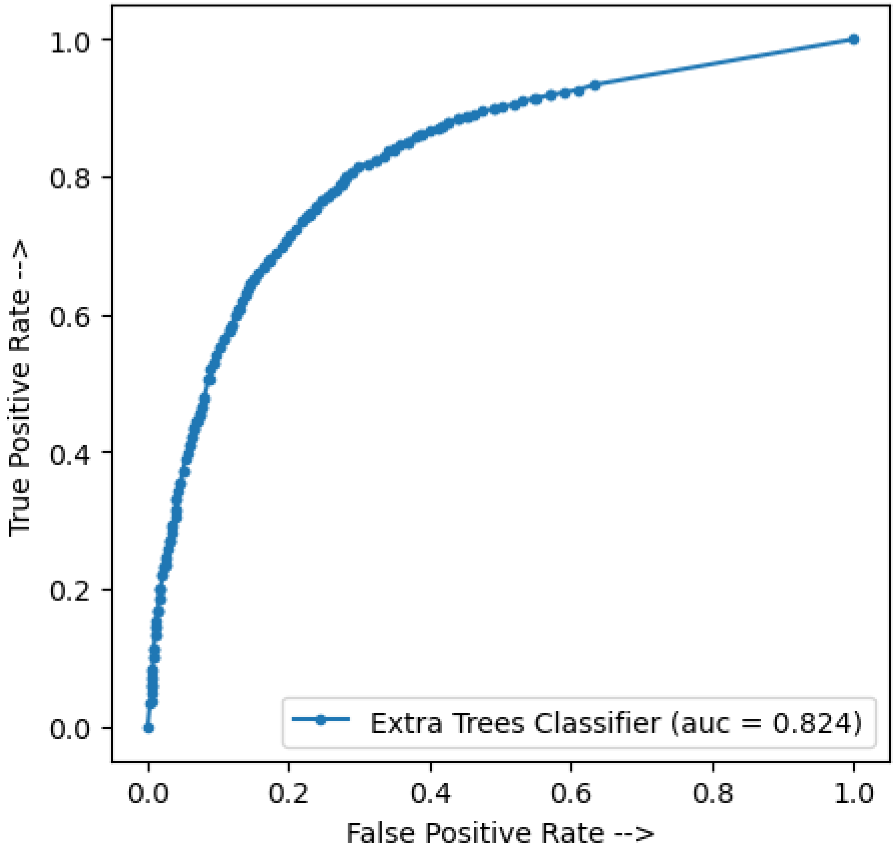
In [41]:

```
skplt.metrics.plot_confusion_matrix(yteste, tp_rfm, normalize=True)
plt.show()
```



In [42]:

```
y_pred_rfm = rfm.predict_proba(xteste)
rfm_fpr,rfm_tpr,thereshold = roc_curve(yteste,y_pred_et[:,1])
auc_rfm = auc(rfm_fpr,rfm_tpr)
plt.figure(figsize=(5, 5), dpi=100)
plt.plot(rfm_fpr,rfm_tpr, marker='.', label='Extra Trees Classifier (auc = %0.3f)' % au
plt.xlabel('False Positive Rate -->')
plt.ylabel('True Positive Rate -->')
plt.legend()
plt.show()
```



Apêndice: testes mostrando variações que não foram aproveitadas no ML acima

1) Tentativa sem a coluna CEP

In [ ]:

```
df_sem_cep = df_ml1[['Regiao','UF','CNAE','Atendida','CodAssunto','SexoConsumidor','Fa
```

In [ ]:

```
df_sem_cep
```

In [ ]:

```
df_sem_cep = pd.get_dummies(df_sem_cep[['Regiao',
                             'UF',
                             'CNAE',
                             'Atendida',
                             'CodAssunto',
                             'SexoConsumidor',
                             'FaixaEtaria','InscritoDAU']])
```

In [ ]:

```
df_sem_cep.shape # a do ml1 tinha 6922 colunas
```

In [ ]:

```
Xdf_sem_cep = df_sem_cep.drop(['Atendida'],axis=1)
ydf_sem_cep = df_sem_cep.Atendida
smt = SMOTE()
Xdf_sem_cep_os,ydf_sem_cep_os = smt.fit_sample(Xdf_sem_cep,ydf_sem_cep) #os de oversamp
counter = Counter(ydf_sem_cep_os)
print(counter)
```

In [ ]:

```
#Train_test_split nessa oversampled
# especificamos o tamanho do test_size = 0.3 pq assim as True/False do ytreinamento e 1
xtreinamentodf_sem_cep, xtestedf_sem_cep, ytreinamentodf_sem_cep, ytestedf_sem_cep = tr
```

ML do df_sem_cep

In [ ]:

```
#Retomamos os train_test_split a partir do oversample ("_os") que já tínhamos feito
#xtreinamentodf_sem_cep, xtestedf_sem_cep, ytreinamentodf_sem_cep, ytestedf_sem_cep= tr
```

In [ ]:

```
# Modelo Extra Trees Classifier
etdf_sem_cep = ExtraTreesClassifier(random_state=0)
etdf_sem_cep = etdf_sem_cep.fit(xtreinamentodf_sem_cep, ytreinamentodf_sem_cep)
print("Acurácia de treinamento: ", etdf_sem_cep.score(xtreinamentodf_sem_cep, ytreiname
Train_predict_etdf_sem_cep = etdf_sem_cep.predict(xtestedf_sem_cep)
print("Acurácia de previsão: ", accuracy_score(ytestedf_sem_cep, Train_predict_etdf_ser
print(classification_report(ytestedf_sem_cep, Train_predict_etdf_sem_cep))
```

In [ ]:

```
# Modelo Logistic Regression
lrdf_sem_cep = LogisticRegression(random_state=0)
lrdf_sem_cep = lrdf_sem_cep.fit(xtreinamentodf_sem_cep, ytreinamentodf_sem_cep)
print("Acurácia de treinamento: ", lrdf_sem_cep.score(xtreinamentodf_sem_cep, ytreiname
Train_predict_lrdf_sem_cep = lrdf_sem_cep.predict(xtestedf_sem_cep)
print("Acurácia de previsão: ", accuracy_score(ytestedf_sem_cep, Train_predict_lrdf_ser
print(classification_report(ytestedf_sem_cep, Train_predict_lrdf_sem_cep))
```

In [ ]:

```
# Modelo Light Gradient Boosting Machine
import lightgbm
from lightgbm import LGBMClassifier
lightgbmdf_sem_cep = LGBMClassifier(random_state=0)
lightgbmdf_sem_cep = lightgbmdf_sem_cep.fit(xtreinamentodf_sem_cep, ytreinamentodf_sem_
print("Acurácia de treinamento: ", lightgbmdf_sem_cep.score(xtreinamentodf_sem_cep, ytr
Train_predict_lightgbmdf_sem_cep = lightgbmdf_sem_cep.predict(xtestedf_sem_cep)
print("Acurácia de previsão: ", accuracy_score(ytestedf_sem_cep, Train_predict_lightgbr
print(classification_report(ytestedf_sem_cep, Train_predict_lightgbmdf_sem_cep))
```

2) Tentativa com LabelEncoder para as de alta cardinalidade

A melhor técnica dispõe que devemos criar label enconders para as variáveis de alta cardinalidade. Não obstante, as nossas variáveis categóricas não podem sofrer o enviesamento: um CNAE 8630502 não é 8630502 vezes melhor ou pior do que o CNAE 0000001. Adotar os label encoders para as varáveis verdadeiramente explicativas - CNAE e CodAssunto - implicaria em um descolamento com a realidade dos problemas dessa natureza.

In [ ]:

```
df_le = df_ml1 #leia-se "dataframe label encoder"
```

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
```

In [ ]:

```
df_le.nunique()
```

In [ ]:

```
colunascategoricas = df_le.select_dtypes('object').columns
colunascategoricas
```

In [ ]:

```
for col in colunascategoricas:
    df_le[col+'_encoded'] = LabelEncoder().fit_transform(df_le[col])
```

In [ ]:

```
df_le
```

In [ ]:

```
# Para definir as colunas que permanecerem no nosso nosso dataframe selecionaremos:
# para de alta cardinalidade, mantemos LabelEncoder;
# para as de baixa e média, criaremos dummies
```

In [ ]:

```
df_le = df_le[['Regiao','UF','CNAE_encoded','Atendida','CodAssunto_encoded','SexoConsur
```

In [ ]:

```
df_le
```

In [ ]:

```
# Pois bem, vamos agora criar dummies para 'Regiao' (5 unique), 'UF' (15), SexoConsumic
```

In [ ]:

```
df_le_du = pd.get_dummies(df_le,
                         columns = ['Regiao',
                                    'UF',
                                    'SexoConsumidor',
                                    'FaixaEtaria'],
                          prefix = ['Regiao',
                                    'UF',
                                    'SexoConsumidor',
                                    'FaixaEtaria'],
                          prefix_sep = '_' )

```

In [ ]:

```
df_le_du.info()
```

In [ ]:

```
df_le_du # leia-se df label encoder com dummies
```

In [ ]:

```
df_le_du.info()
```

Agora, então, temos dummies para as de baixa e média cardinalidade: 'Regiao' (5 unique), 'UF' (15 unique), SexoConsumidor' (2 unique) e 'FaixaEtaria' (7); e label encoder para as de alta cardinalidade 'CNAE_encoded' (368 unique), 'CodAssunto_encoded'(175 unique) e CEP (6354 unique)

In [ ]:

```
Xdf_le_du = df_le_du.drop(['Atendida'],axis=1)
ydf_le_du = df_le_du.Atendida
smt = SMOTE()
Xdf_le_du_os,ydf_le_du_os = smt.fit_sample(Xdf_le_du,ydf_le_du) #os de oversampled
counter = Counter(ydf_le_du_os)
print(counter)
```

In [ ]:

```
#Train_test_split nessa oversampled
# especificamos o tamanho do test_size = 0.3 pq assim as True/False do ytreinamento fic
#True/False do yteste também ficam iguais
xtreinamentodf_le_du, xtestedf_le_du, ytreinamentodf_le_du, ytestedf_le_du = train_test
```

In [ ]:

```
#Retomamos os train_test_split a partir do oversample ("_os") que já tínhamos feito
#xtreinamentodf_le_du, xtestedf_le_du, ytreinamentodf_le_du, ytestedf_le_du = train_tes
```

ML do df_le_du ("df label encoder dummies")

In [ ]:

```
# Modelo Extra Trees Classifier
etdf_le_du = ExtraTreesClassifier(random_state=0)
etdf_le_du = etdf_le_du.fit(xtreinamentodf_le_du, ytreinamentodf_le_du)
print("Acurácia de treinamento: ", etdf_le_du.score(xtreinamentodf_le_du, ytreinamentod
Train_predict_etdf_le_du = etdf_le_du.predict(xtestedf_le_du)
print("Acurácia de previsão: ", accuracy_score(ytestedf_le_du, Train_predict_etdf_le_du
print(classification_report(ytestedf_le_du, Train_predict_etdf_le_du))
```

In [ ]:

```
# Modelo Logistic Regression
lrdf_le_du = LogisticRegression(random_state=0)
lrdf_le_du = lrdf_le_du.fit(xtreinamentodf_le_du, ytreinamentodf_le_du)
print("Acurácia de treinamento: ", lrdf_le_du.score(xtreinamentodf_le_du, ytreinamentod
Train_predict_lrdf_le_du = lrdf_le_du.predict(xtestedf_le_du)
print("Acurácia de previsão: ", accuracy_score(ytestedf_le_du, Train_predict_lrdf_le_du
print(classification_report(ytestedf_le_du, Train_predict_lrdf_le_du))
```

In [ ]:

```
#Modelo Light Gradient Boosting Machine
import lightgbm
from lightgbm import LGBMClassifier
lightgbmdf_le_du = LGBMClassifier(random_state=0)
lightgbmdf_le_du = lightgbmdf_le_du.fit(xtreinamentodf_le_du, ytreinamentodf_le_du)
print("Acurácia de treinamento: ", lightgbmdf_le_du.score(xtreinamentodf_le_du, ytreina
Train_predict_lightgbmdf_le_du = lightgbmdf_le_du.predict(xtestedf_le_du)
print("Acurácia de previsão: ", accuracy_score(ytestedf_le_du, Train_predict_lightgbmdf
print(classification_report(ytestedf_le_du, Train_predict_lightgbmdf_le_du))
```

Não obstante melhorar o desempenho dos modelos Extra Trees e LightGBM, houve piora no modelo escolhido, o de Regressão Logística.