ITBA
Instituto Tecnológicc
de Buenos Aires

PRESENTACION FINAL

Sofía Feilbogen - L. 61889

ÍNDICE

Introducción

Datos del cliente

CLIENT NÚM: identificador del cliente

Attrition Flag: bandera de desgaste; si la cuenta está cerrada: 1 sino 0

Customer Age: edad del cliente

Gender: M masculino; F femenino

Dependent Count: número de personas dependientes del cliente: niños, adultos dependientes

Education Level: nivel educativo XX

Marital Status: estado matrimonial: Casado, soltero, divorciado,desconocido

Income Category: categoria de ingreso: $40K, $40K - 60K, $60K - $80K, $80K-$120K, > $120K, desconocido

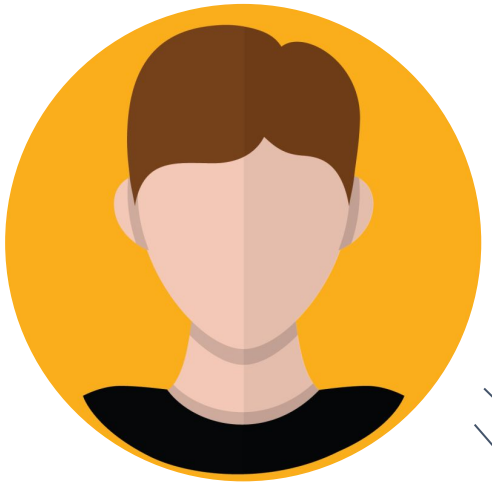
Card Category: categoría de tarjeta: Blue, Silver, Gold, Platinum

Months on book: meses de relación con el banco

10127 registros. 23 variables.

Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1
Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2

Datos del cliente



- Total Relationship Count: número total de productos retenidos por el cliente
- Months Inactive 12 mon: meses de inactividad en los últimos 12 meses
- Contacts Count 12 mon: numero de contactos en los últimos 12 meses
- Credit Limit: limite de credito
- Total Revolving Bal: saldo rotatorio total en la tarjeta de crédito
- Avg_Open_To_Buy
- Total Amt Chng Q4 Q1: cambio en el monto de la transacción (Q4 sobre Q1)
- Total Trans Amt: importe total de transacciones en los últimos 12 meses
- Total Trans Ct: recuento total de transacciones en los últimos 12 meses
- Total Ct Chng Q4 Q1
- Avg Utilization Ratio

Objetivos del trabajo

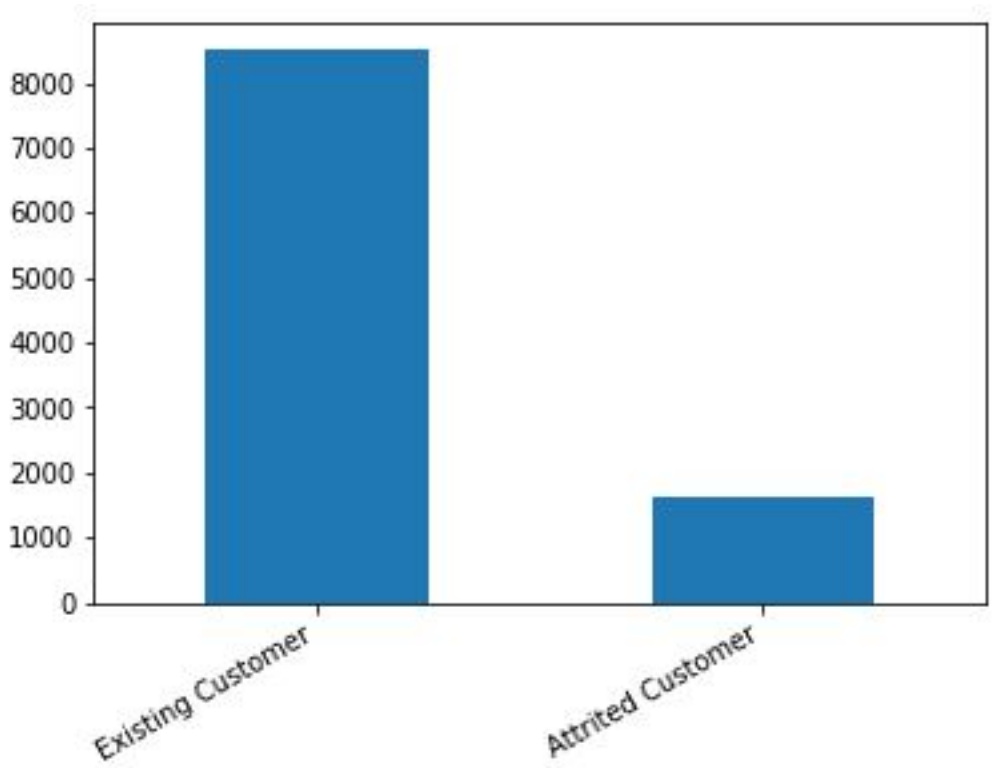
Entender qué variables afectan a un cliente para que sea perdido.

Encontrar el perfil del cliente perdido.

De esta forma entendemos sobre qué tenemos que poner foco para que un cliente existente no se pierda y así retenerlo.

De esta forma también podemos categorizar al cliente, dejar un registro de que es posible que se pierda o no en un futuro y estar más atento a los que se pierdan posiblemente.

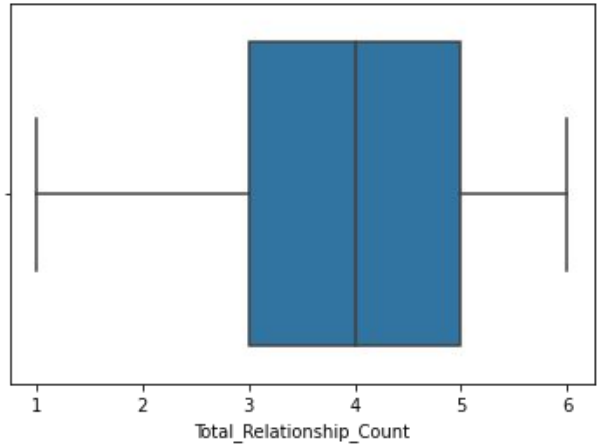
Características del trabajo

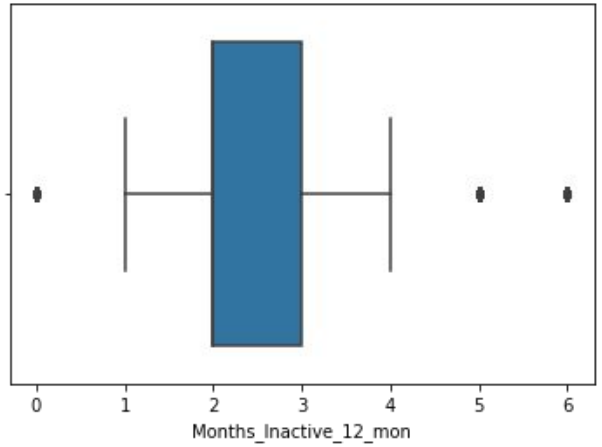


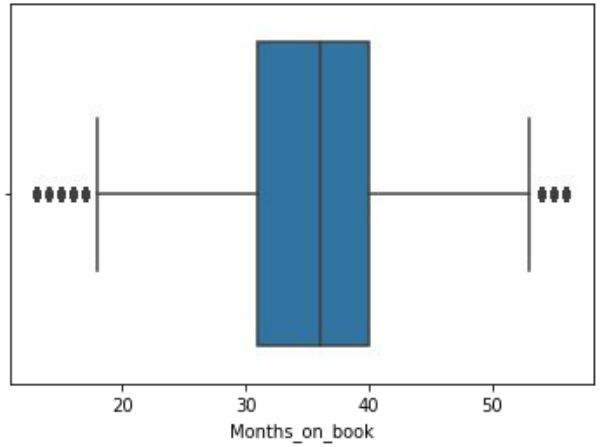
Existing Customer 8500
Attrited Customer 1627
20% de 10127= 2025,4(moderately imbalanced)

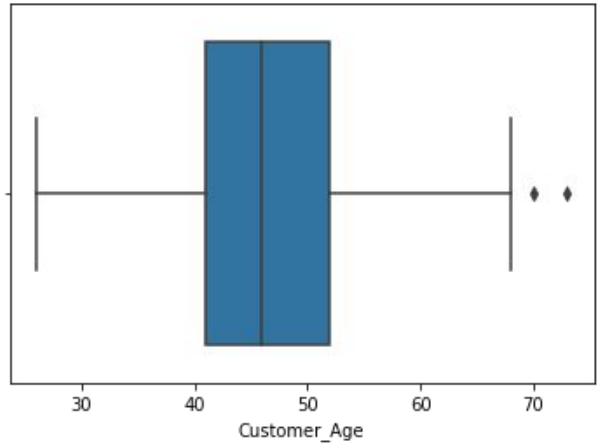
Datos asimétricos y desbalanceados

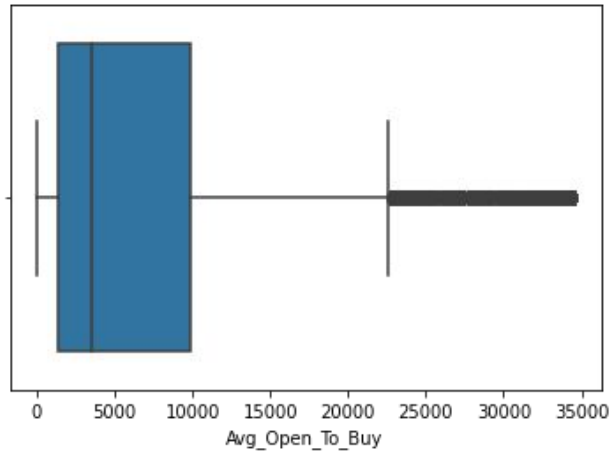
Estadísticas descriptivas principales

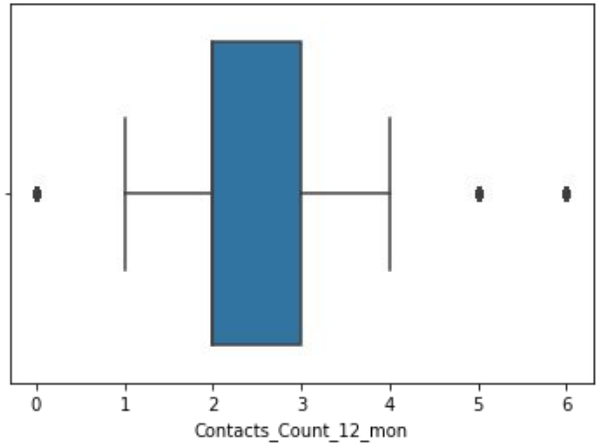

1
2
3
4
5
6
Total_Relationship_Count

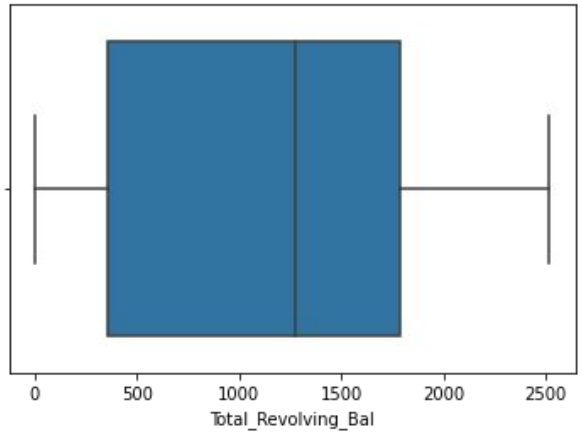

0
1
2
3
4
5
6
Months_Inactive_12_mon

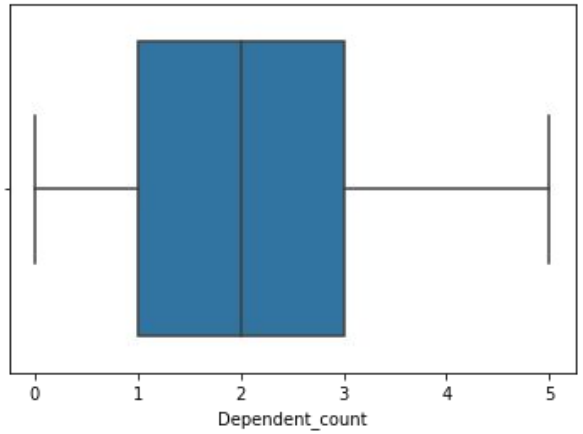

20
30
40
50
Months_on_book

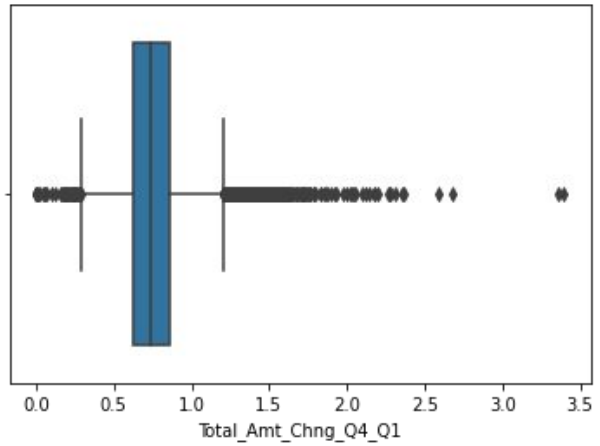

30
40
50
60
70
Customer_Age

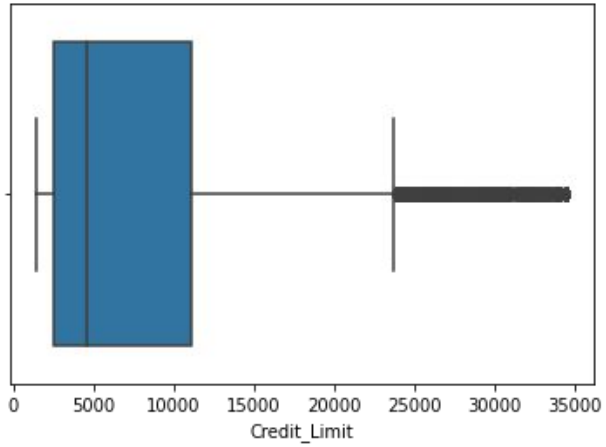

0
5000
10000
15000
20000
25000
30000
35000
Avg_Open_To_Buy

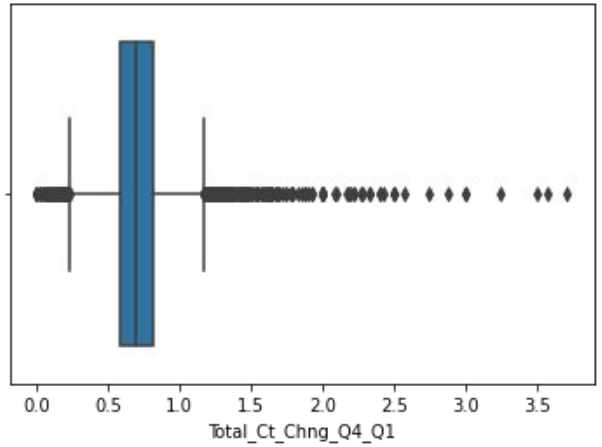

0
1
2
3
4
5
6
Contacts_Count_12_mon

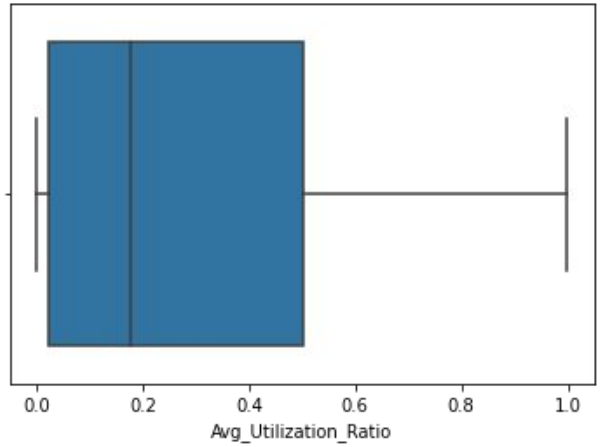

0
500
1000
1500
2000
2500
Total_Revolving_Bal

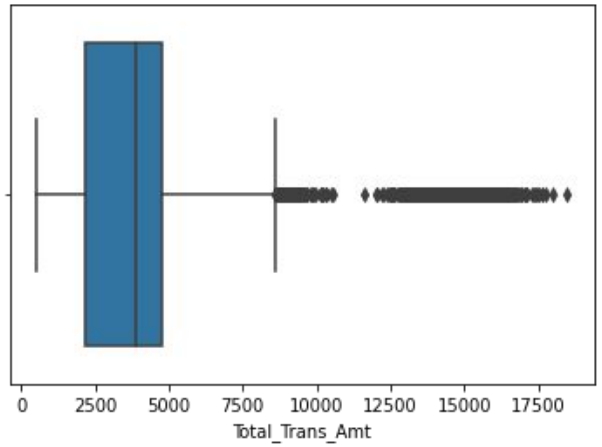

0
1
2
3
4
5
Dependent_count

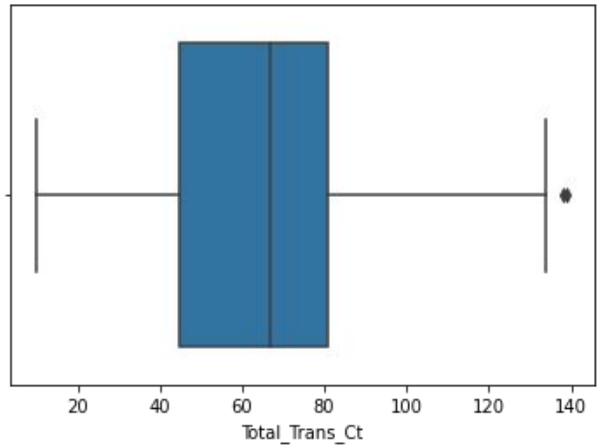

0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Total_Amt_Chng_Q4_Q1











- No se encuentran missings
- Se encuentran outliers en 10 variables

Education Level, Marital Status, Income Category → "Unknown" → NaN

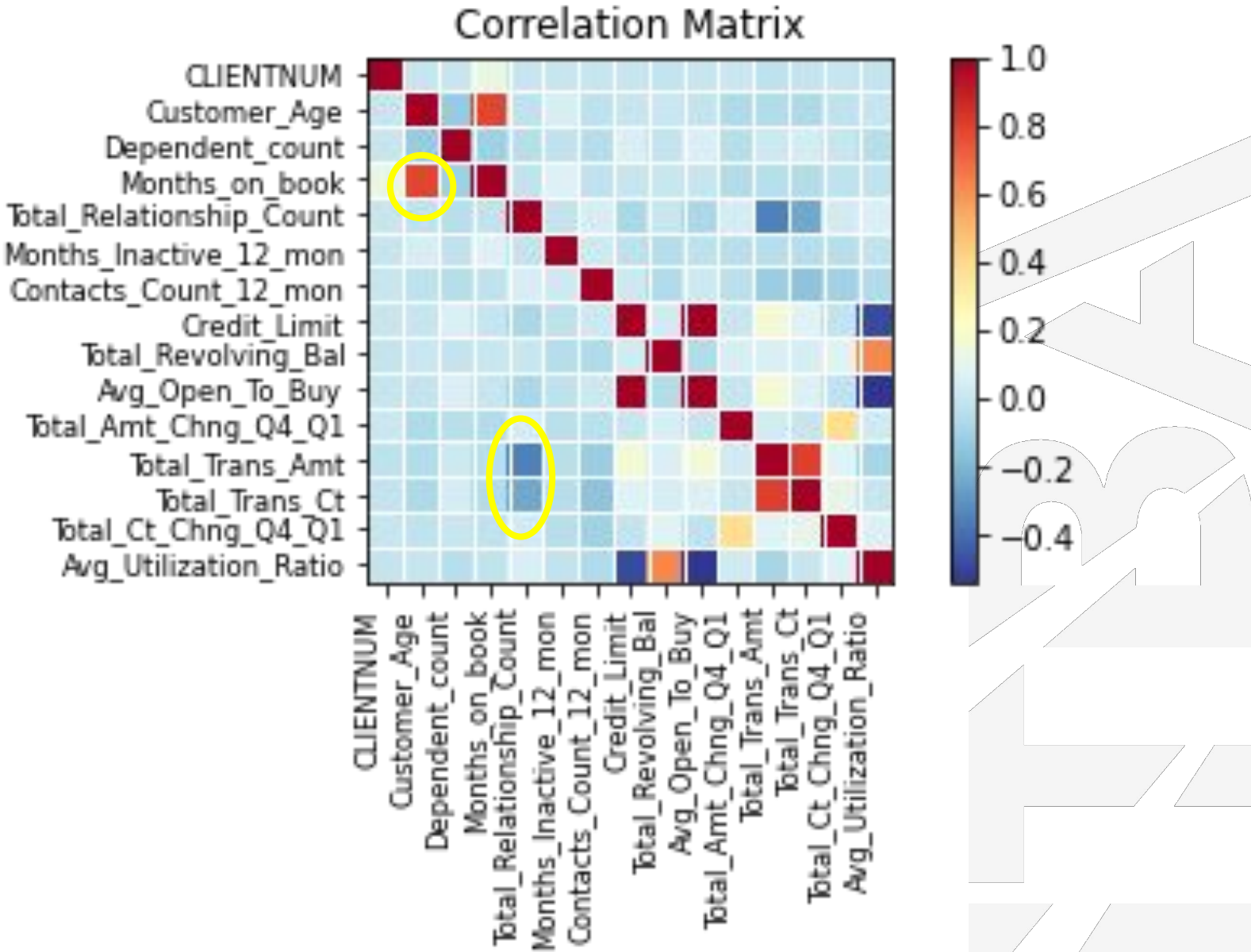
Edad más chica: 26

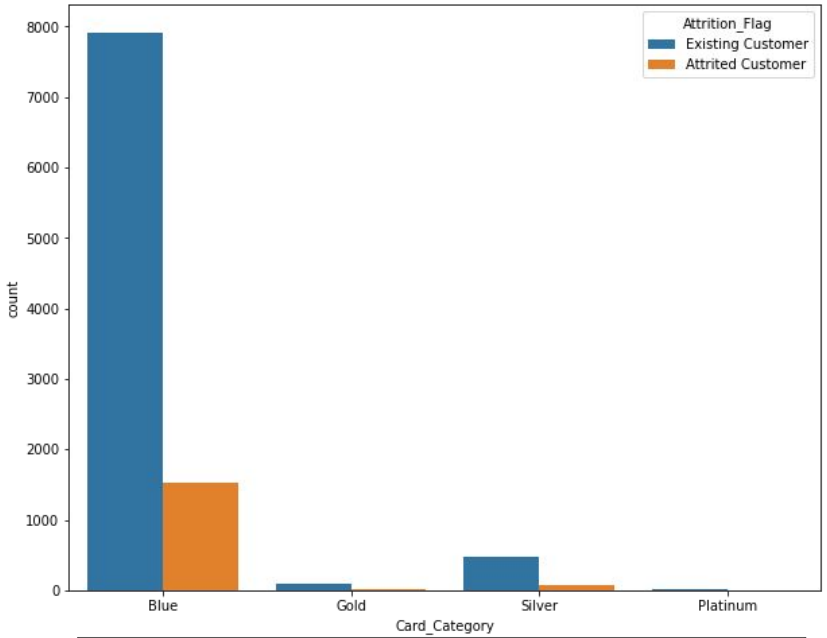
	CLIENTNUM	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Contacts_Count_12_mon
count	1.012700e+04	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000
mean	7.391776e+08	46.325960	2.346203	35.928409	3.812580	2.341167	2.455317
std	3.690378e+07	8.016814	1.298908	7.986416	1.554408	1.010622	1.106225
min	7.080821e+08	26.000000	0.000000	13.000000	1.000000	0.000000	0.000000
25%	7.130368e+08	41.000000	1.000000	31.000000	3.000000	2.000000	2.000000
50%	7.179264e+08	46.000000	2.000000	36.000000	4.000000	2.000000	2.000000
75%	7.731435e+08	52.000000	3.000000	40.000000	5.000000	3.000000	3.000000
max	8.283431e+08	73.000000	5.000000	56.000000	6.000000	6.000000	6.000000

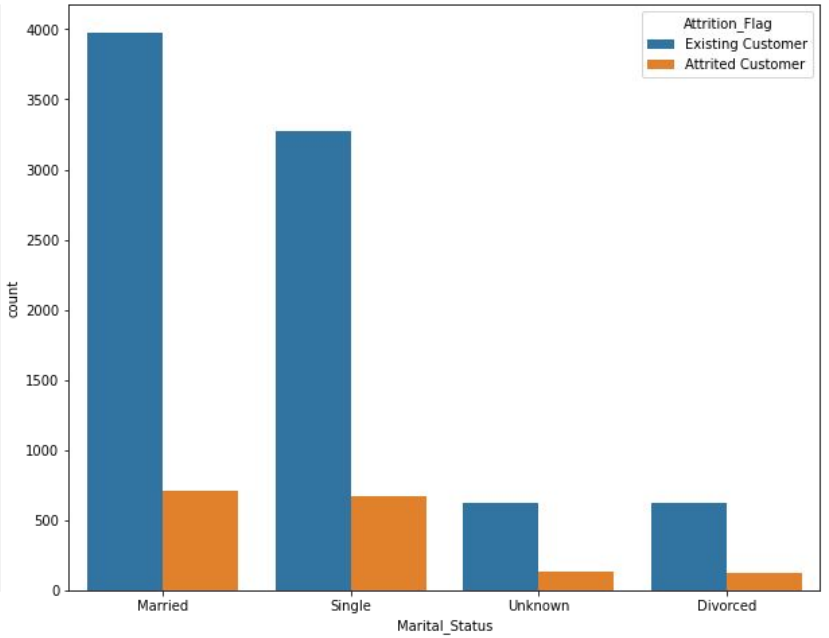
Credit_Limit	Total_Revolving_Bal	Avg_Open_To_Buy	Total_Amt_Chng_Q4_Q1	Total_Trans_Amt	Total_Trans_Ct	Total_Ct_Chng_Q4_Q1	Avg_Utilization_Ratio
10127.000000	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000	10127.000000
8631.953698	1162.814061	7469.139637	0.759941	4404.086304	64.858695	0.712222	0.274894
9088.776650	814.987335	9090.685324	0.219207	3397.129254	23.472570	0.238086	0.275691
1438.300000	0.000000	3.000000	0.000000	510.000000	10.000000	0.000000	0.000000
2555.000000	359.000000	1324.500000	0.631000	2155.500000	45.000000	0.582000	0.023000
4549.000000	1276.000000	3474.000000	0.736000	3899.000000	67.000000	0.702000	0.176000
11067.500000	1784.000000	9859.000000	0.859000	4741.000000	81.000000	0.818000	0.503000
34516.000000	2517.000000	34516.000000	3.397000	18484.000000	139.000000	3.714000	0.999000

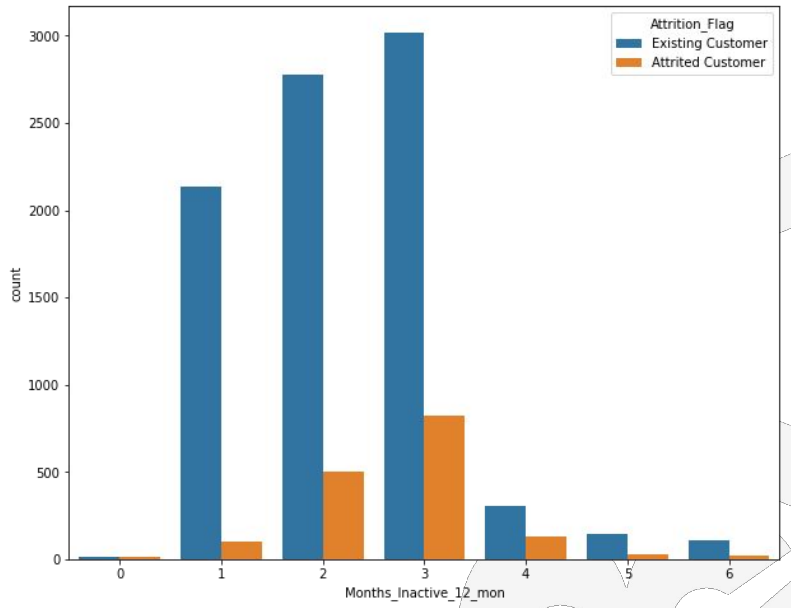
Data discovery

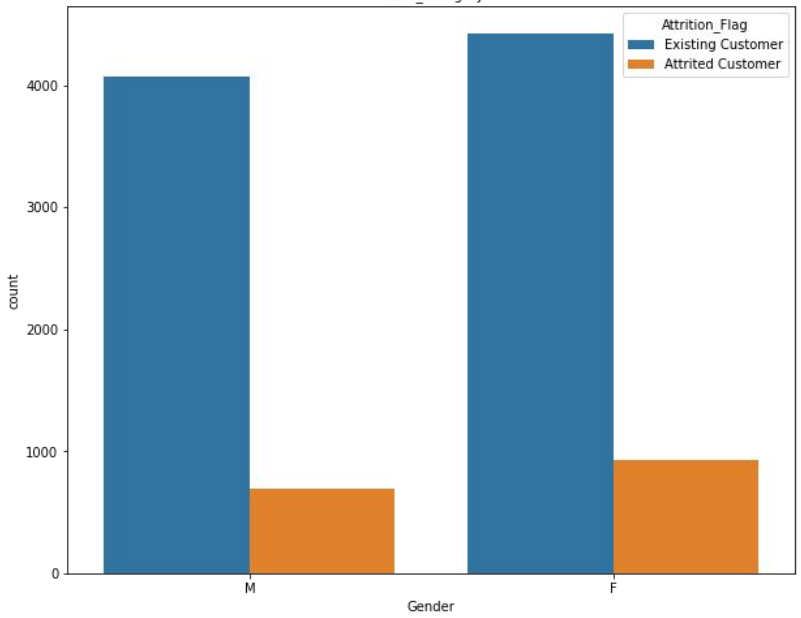
Matriz de correlación de Pearson

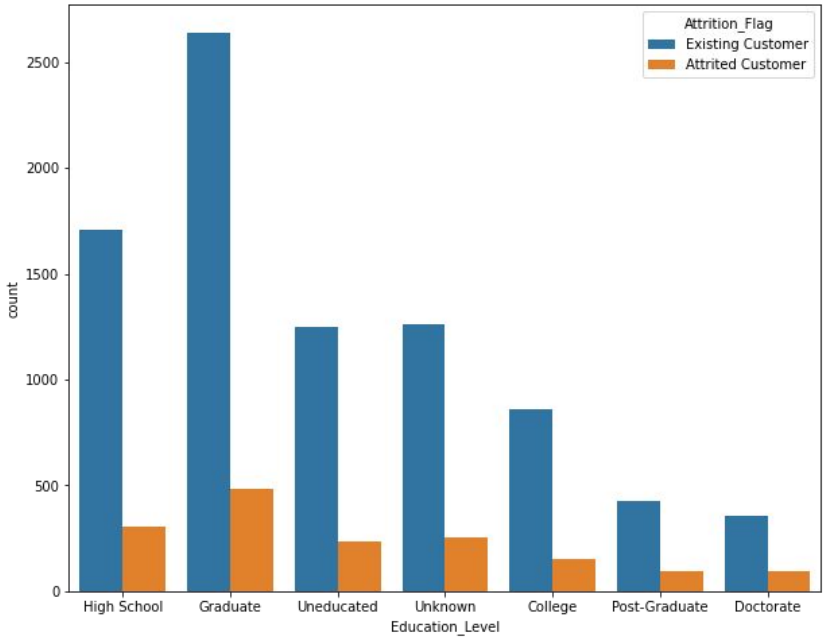




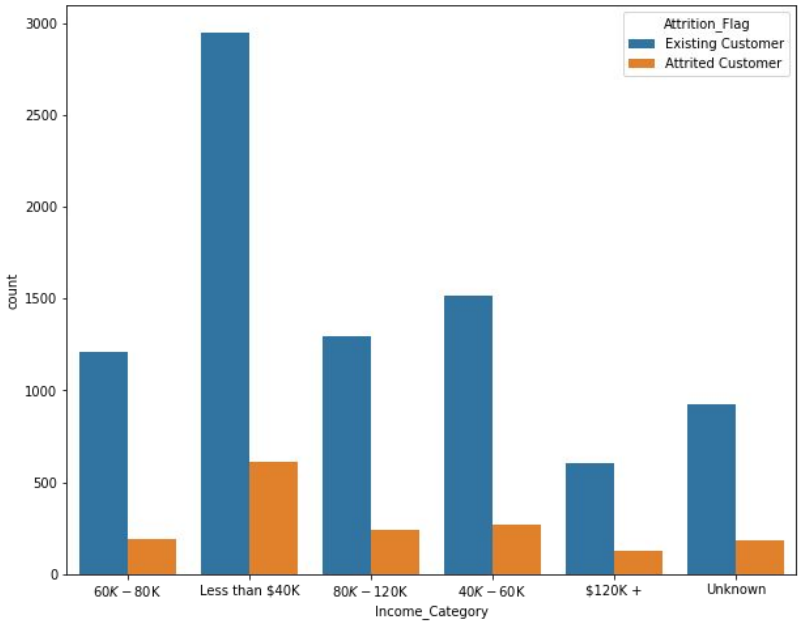


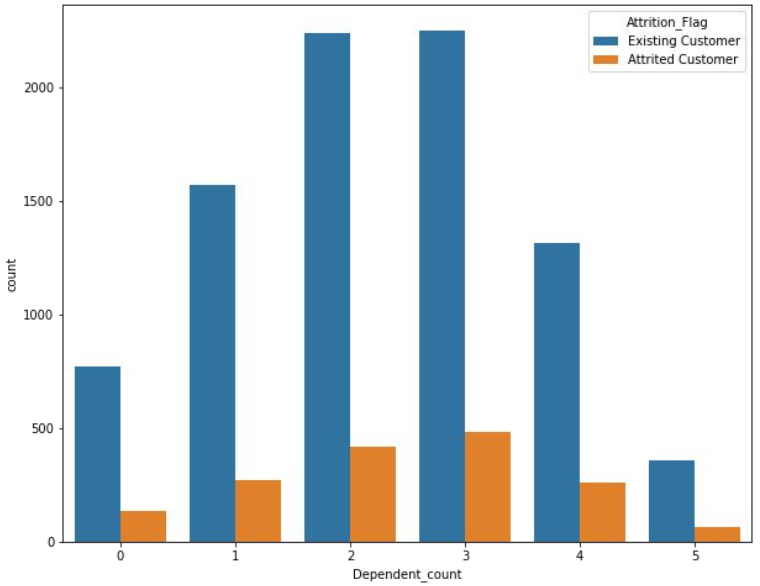


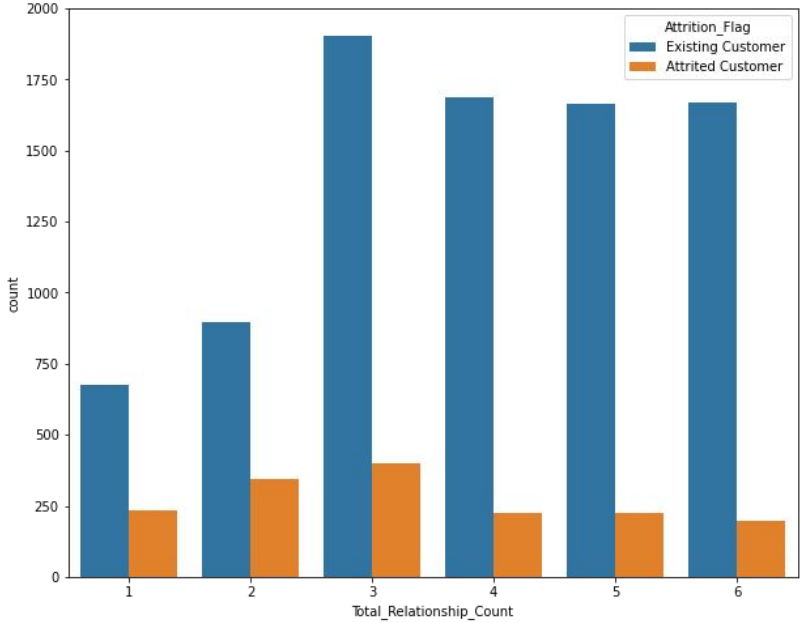


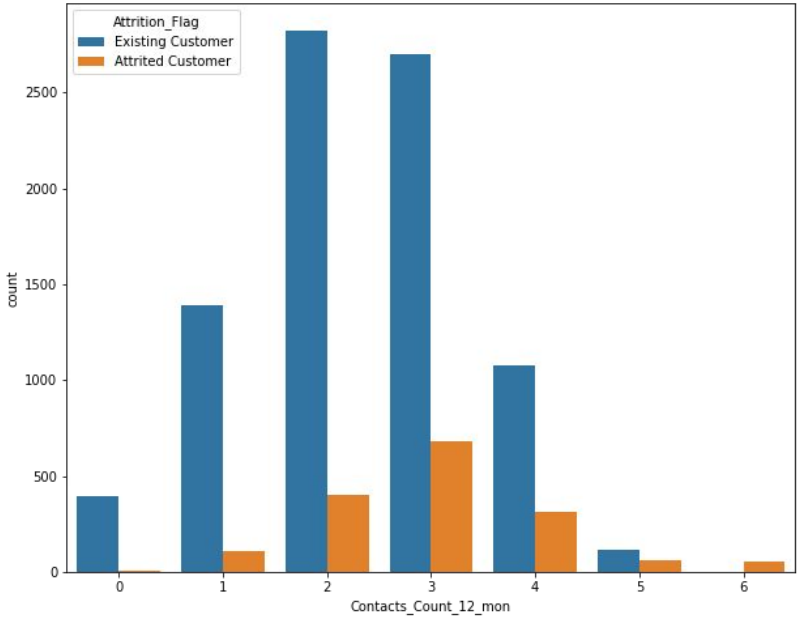


Card category: blue
Marital status: married / single
Months inactive 12 mon: 2 / 3
Gender: M / F
Education level: High school / graduate

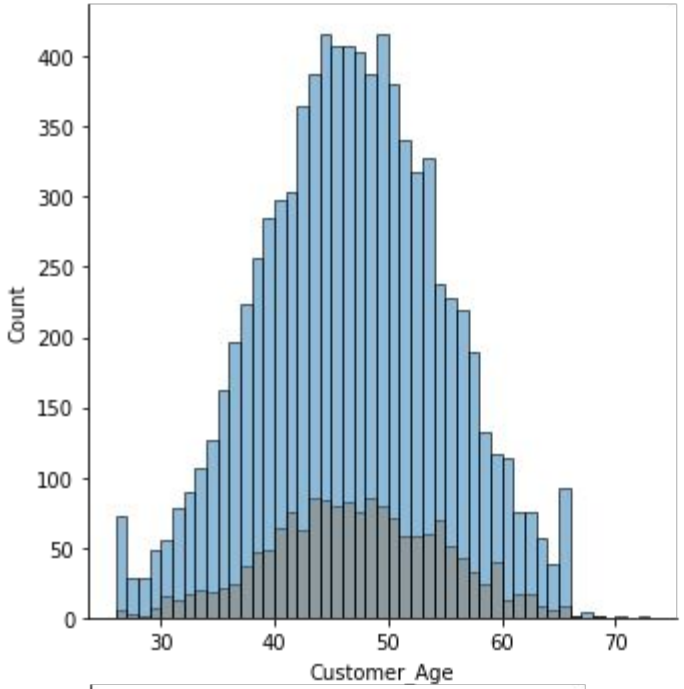


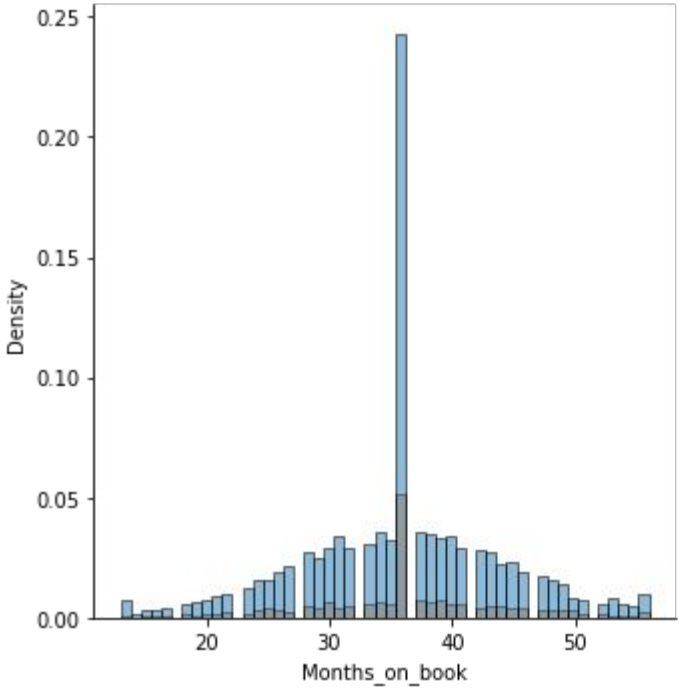


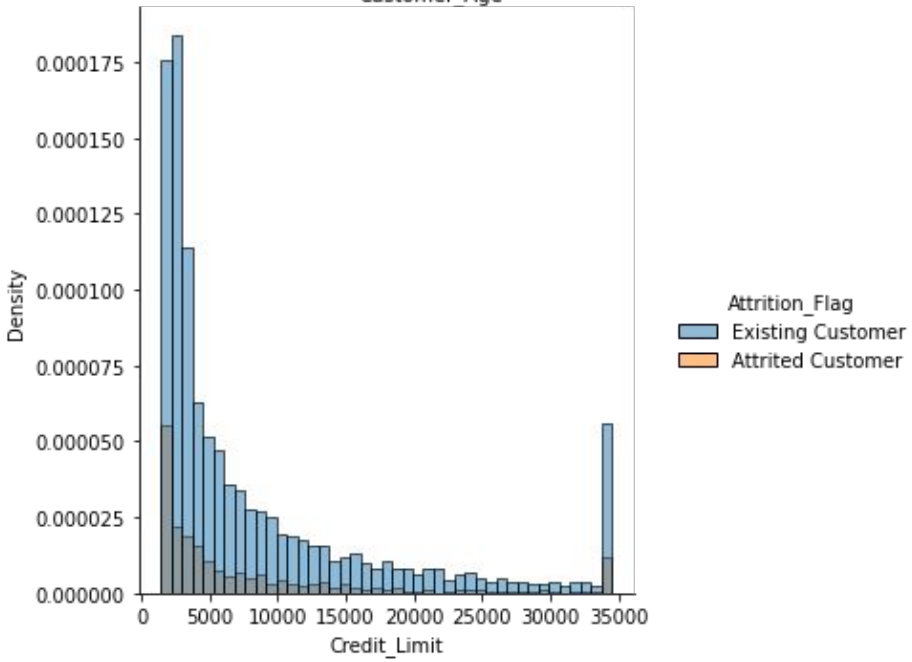


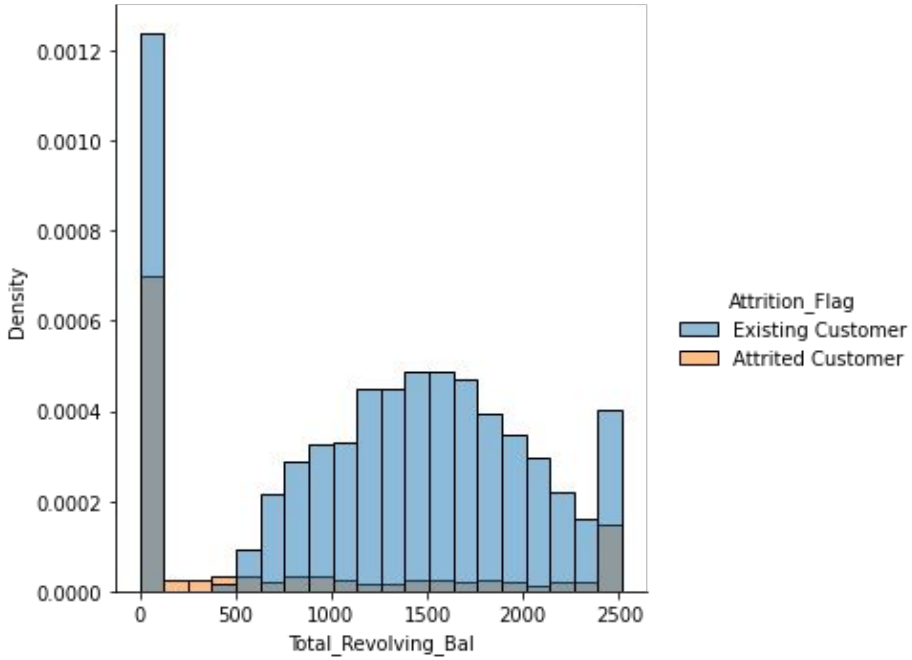


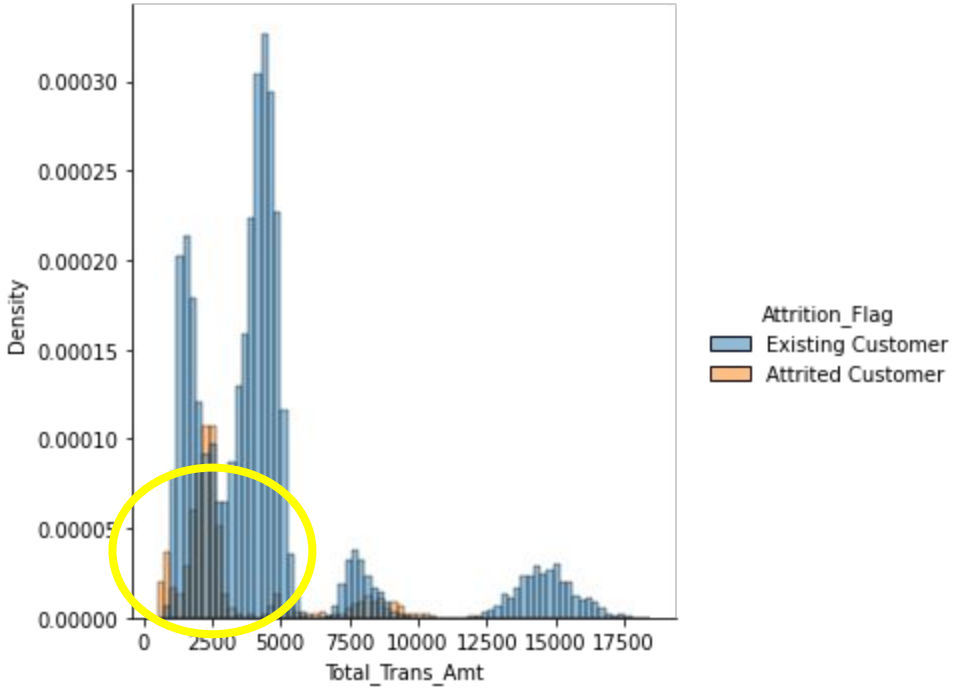
Less than $40K
Dependent count: 2 / 3
Total relationship count: 2 / 3
Contact count: 2 / 3 / 4

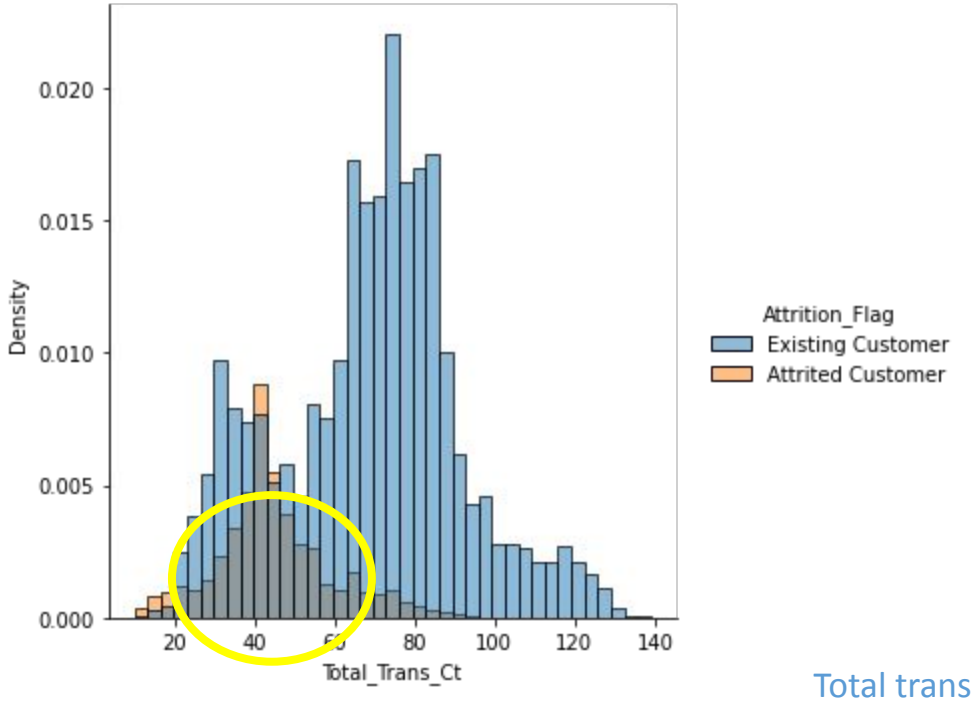

Count
Customer_Age
Attrition_Flag
Existing Customer
Attrited Customer


Density
Months_on_book
Attrition_Flag
Existing Customer
Attrited Customer

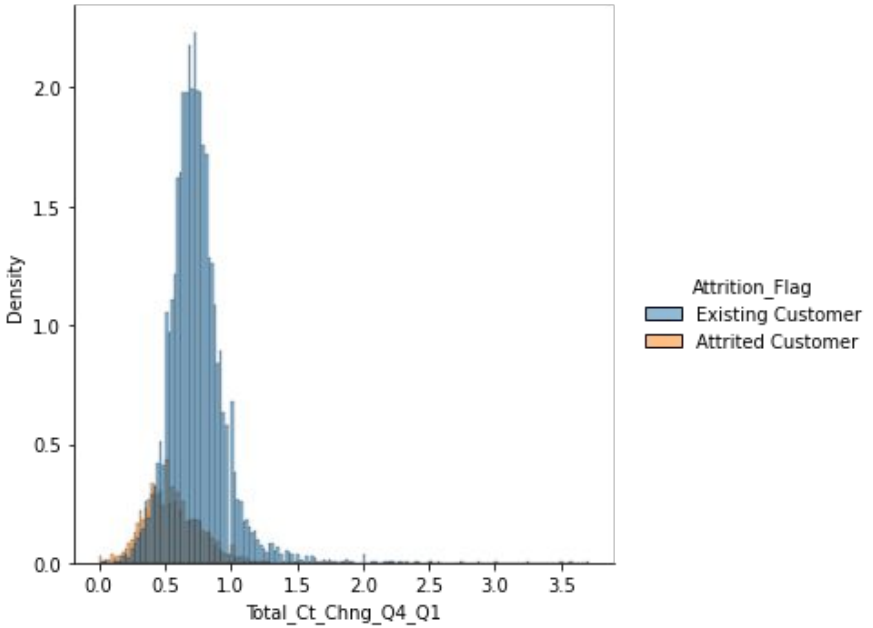

Density
Credit_Limit
Attrition_Flag
Existing Customer
Attrited Customer

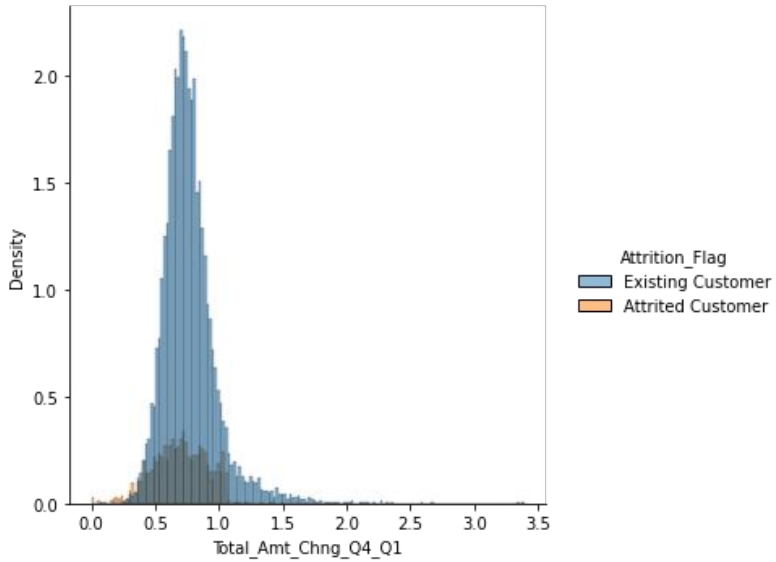

Density
Total_Revolving_Bal
Attrition_Flag
Existing Customer
Attrited Customer



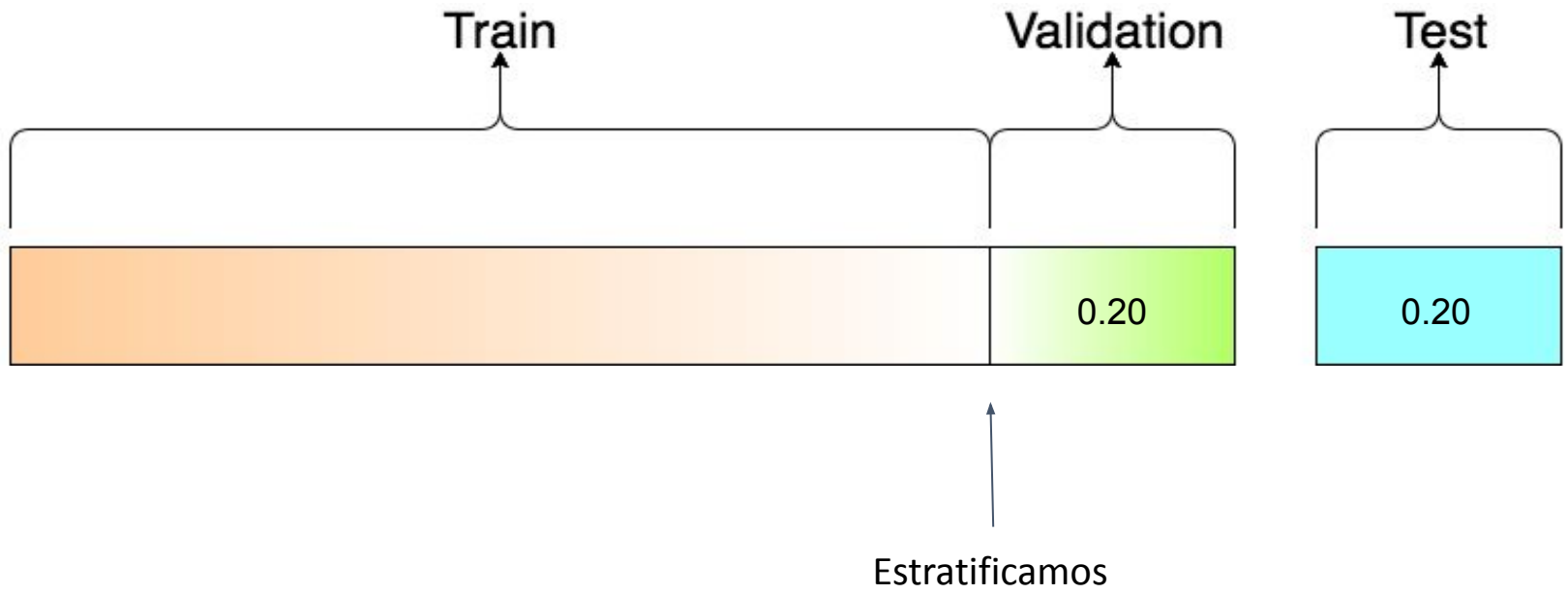


Total trans amt: 0-3000
Total trans ct: 0-1000





Partición

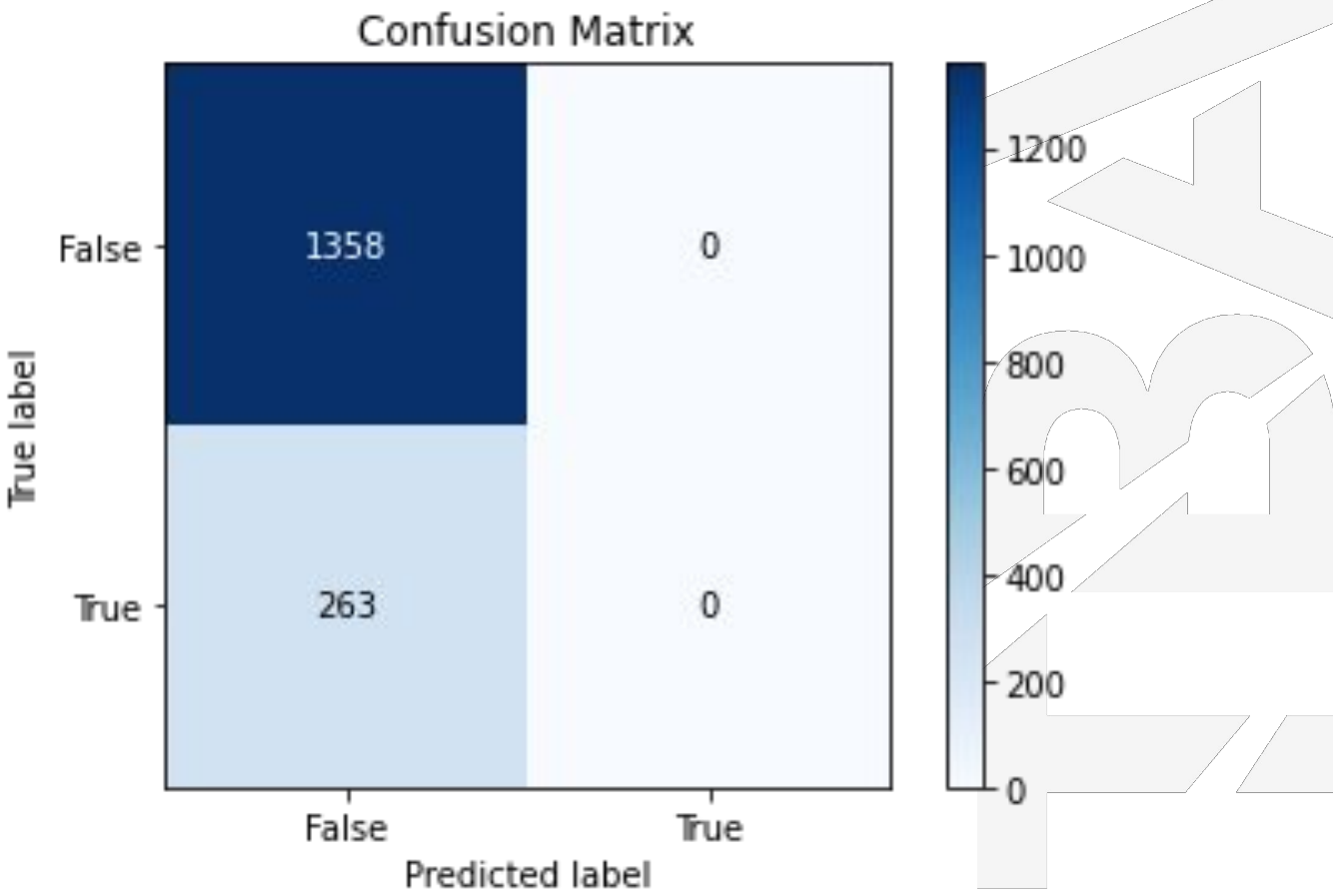

Train
Validation
Test
0.20
0.20
Estratificamos

Transformamos a False (0) la clase mayoritaria (Existing Customer) y a True (1) la minoritaria.

y	Existing Customer	0.837921
	Attrited Customer	0.162079
y_train	Existing Customer	0.837963
	Attrited Customer	0.162037
y_val	Existing Customer	0.837754
	Attrited Customer	0.162246

Accuracy de predecir la clase mayoritaria:
0.83775447254781

raw frequencies:
[5430 1050]
class weights:
[0.59668508 3.08571429]
[3240. 3240.]



Wi=cantidad de observaciones/(cantidad de clases x frecuencia de clases)

Pipeline

```
Pipeline
DropFeatures
DropFeatures(features_to_drop=['CLIENTNUM',
                               'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1',
                               'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2'])
RandomSampleImputer
RandomSampleImputer(variables=['Education_Level', 'Marital_Status',
                               'Income_Category'])
RareLabelEncoder
RareLabelEncoder(n_categories=1, tol=0.006172077521293668,
                 variables=['Gender', 'Education_Level', 'Marital_Status',
                            'Income_Category', 'Card_Category'])
OrdinalEncoder
OrdinalEncoder(variables=['Gender', 'Education_Level', 'Marital_Status',
                          'Income_Category', 'Card_Category'])
Winsorizer
Winsorizer(add_indicators=True, missing_values='ignore', tail='both',
           variables=['Customer_Age', 'Dependent_count', 'Months_on_book',
                      'Total_Relationship_Count', 'Months_Inactive_12_mon',
                      'Contacts_Count_12_mon', 'Credit_Limit',
                      'Total_Revolving_Bal', 'Avg_Open_To_Buy',
                      'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
                      'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
                      'Avg_Utilization_Ratio'])
```

Winsorizer

- Cola derecha: mean + 3* std
- Cola izquierda: mean - 3* std

	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Contacts_Count_12_mon	Credit_Limit	Total_Revolving_Bal	Avg_Open_To_Buy
8951	52.0000	0	2	2	0	2	0	37	1	3.0000	1.0000	34516.0000	1369	33147.0000
7232	49.0000	0	2	2	0	2	0	38	3	4.0000	3.0000	34516.0000	0	34516.0000
8861	55.0000	0	3	3	2	4	0	44	2	2.0000	3.0000	6455.0000	1837	4618.0000
2112	53.0000	0	4	2	0	2	0	36	3	2.0000	2.0000	3924.0000	2517	1407.0000
4361	46.0000	1	3	1	0	3	0	38	4	2.0000	2.0000	1781.0000	1315	466.0000

Total_Amt_Chng_Q4_Q1	Total_Trans_Amt	Total_Trans_Ct	Total_Ct_Chng_Q4_Q1	Avg_Utilization_Ratio	Customer_Age_right	Dependent_count_right	Months_on_book_right	Total_Relationship_Count_right	Months_Inactive_12_mon_right
0.7640	7745.0000	82	0.6400	0.0400	0.0000	0.0000	0.0000	0.0000	0.0000
0.4820	1592.0000	35	0.3460	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.7170	8001.0000	99	0.7070	0.2850	0.0000	0.0000	0.0000	0.0000	0.0000
0.5110	1417.0000	30	0.6670	0.6410	0.0000	0.0000	0.0000	0.0000	0.0000
0.7040	4775.0000	83	0.7290	0.7380	0.0000	0.0000	0.0000	0.0000	0.0000

Contacts_Count_12_mon_right	Credit_Limit_right	Total_Revolving_Bal_right	Avg_Open_To_Buy_right	Total_Amt_Chng_Q4_Q1_right	Total_Trans_Amt_right	Total_Trans_Ct_right	Total_Ct_Chng_Q4_Q1_right	Avg_Utilization_Ratio_right
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Modelos

Métricas de clasificación

Al ser datos asimétricos(nos interesa más la clase positiva), utilizamos el F score para medir la capacidad de clasificación del modelo.

La precisión es cuántos de los que yo identifique como positivos eran verdaderamente positivos

El recall es cuántos de los positivos yo capturo, cuantos los identifico.

El F-score es la media geométrica de precisión y recordación. Se encuentra entre la precisión y la recuperación.

Valor beta default 1 dándole mismo peso a recall como a la precisión

$$\text{precision} = \frac{\text{tp}}{\text{tp} + \text{fp}} \qquad \text{recall} = \frac{\text{tp}}{\text{tp} + \text{fn}} \qquad F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Métricas de performance

AUPROC: para medir la bondad global del modelo, para medir qué tan bueno es el score utilizamos la curva de AUPROC.

AUROC evalúa FPR (bondad para captar negativos) y TNR (bondad para captar positivos) con la misma ponderación. La curva AUPROC a diferencia de la AUROC es sensible al desbalance y predice con precisión la clase minoritaria. Se utiliza para datos asimétricos y desbalanceados como lo es en nuestro caso.

Es más importante medir la clase minoritaria (1) ya que buscamos encontrar las razones de por que se pierden los clientes. Entonces utilizamos Area Under the Precision-Recall Curve.

AUROC utiliza el FPR=FP/(FP+TN). En estos casos TN es grande entonces baja su valor y lo vuelve poco informativo.

AUPROC trabaja con el TPR y la precisión relacionada con los datos positivos (minorías ambos) cambian sus ejes.

LGBMClassifier

num_leaves: número máximo de hojas

min_child_samples: número minimo de data necesaria en una hoja

max_depth: número máximo de profundidad del árbol

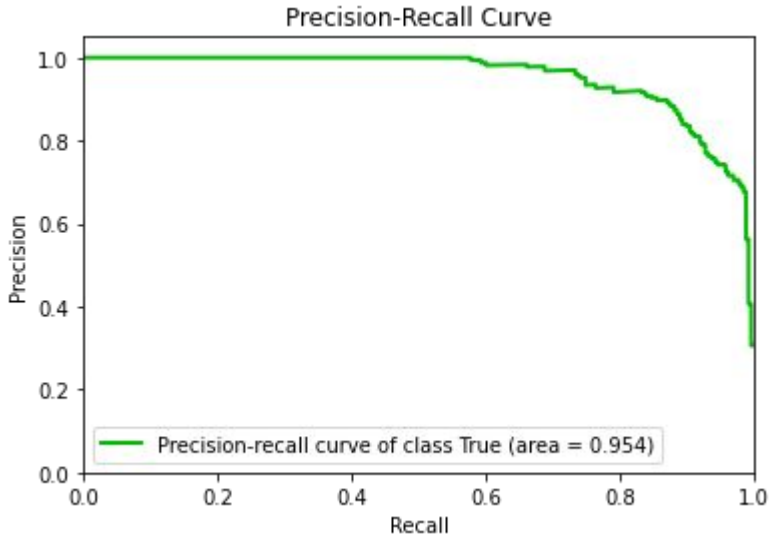
objective: "binary": clasificación binaria

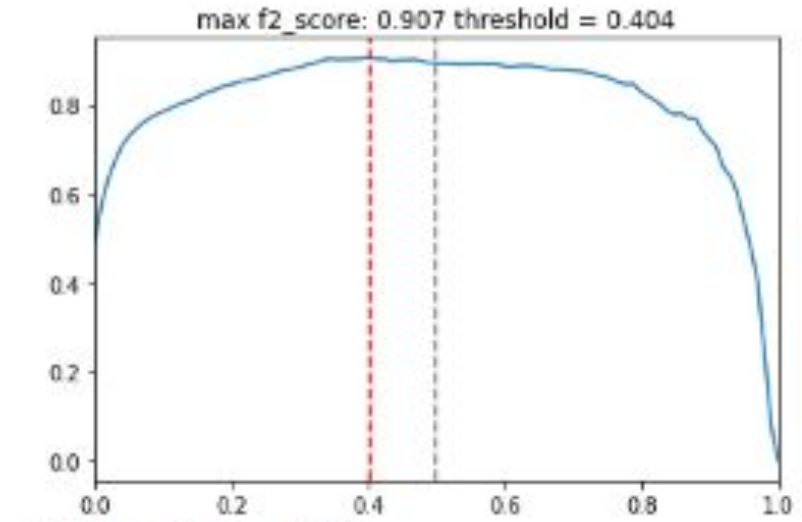
class_weight: balanced

```
param_gridLGBM ={'LGBM__num_leaves': [5,10,20],
                 'LGBM__min_child_samples': [5,10,15],
                 'LGBM__max_depth': [5,10,20],
                }
```

```
gridsearch1.best_params_
```

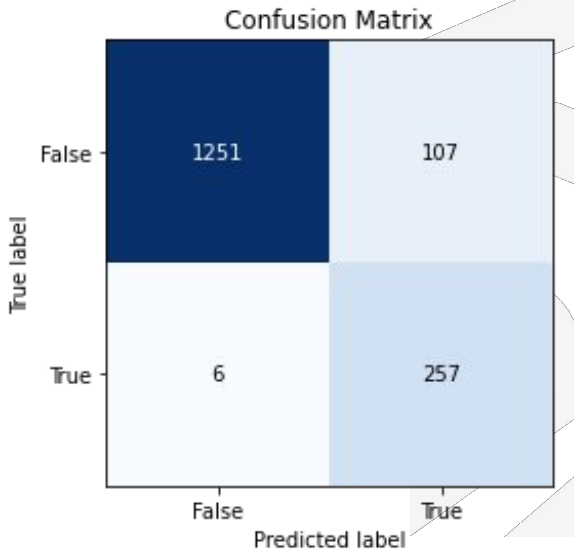
```
{'LGBM__max_depth': 5, 'LGBM__min_child_samples': 5, 'LGBM__num_leaves': 5}
```





threshold = 0.404
accuracy: 0.930
f2: 0.907
AUPRC: 0.954
threshold = 0.500
accuracy: 0.941
f2: 0.894
AUPRC: 0.954

precision = 0.7060
recall = 0.9772
f1 = 0.8198



Decision Tree Classifier

min_samples_leaf: número mínimo de registros requeridos para que se cree una hoja

max_depth: número máximo de profundidad del árbol

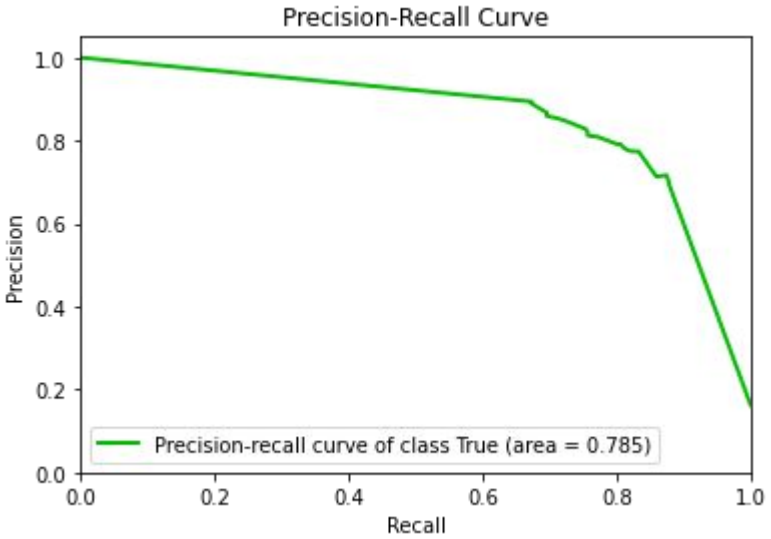
criterion: función de medida de calidad del corte

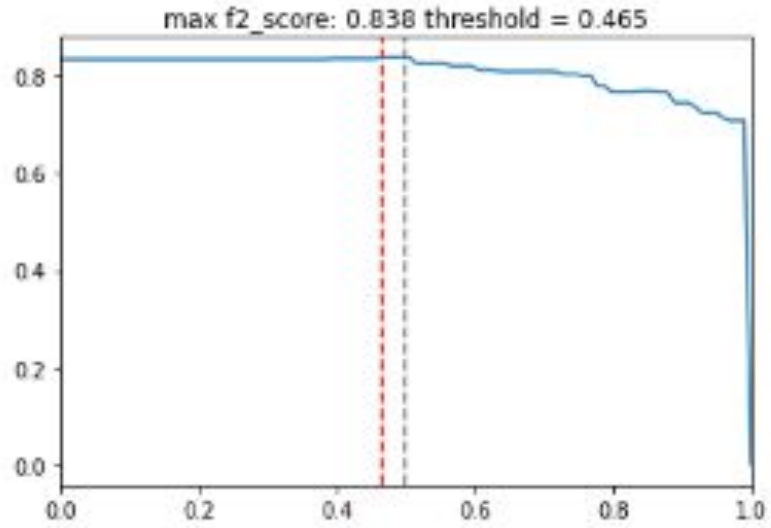
class_weight: balanced

```
parameters={
    'max_depth': [2, 5, 20],
    'min_samples_leaf': [5, 10, 20, 100],
    'criterion': ["gini", "entropy"],
    "class_weight":["balanced"]
}
```

```
search3.best_params_
```

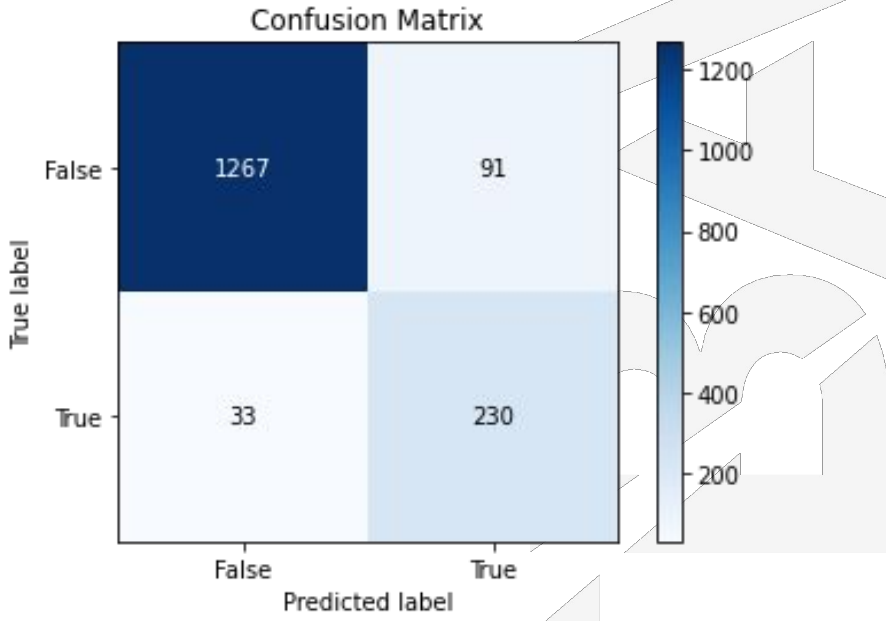
```
{'class_weight': 'balanced',
 'criterion': 'gini',
 'max_depth': 20,
 'min_samples_leaf': 5}
```






```
### threshold = 0.465
accuracy: 0.924
f2: 0.838
AUPRC: 0.785
### threshold = 0.500
accuracy: 0.924
f2: 0.838
AUPRC: 0.785
```

```
precision = 0.7165
recall = 0.8745
f1 = 0.7877
```



Extra Trees Classifier

max_depth: número máximo de profundidad del árbol

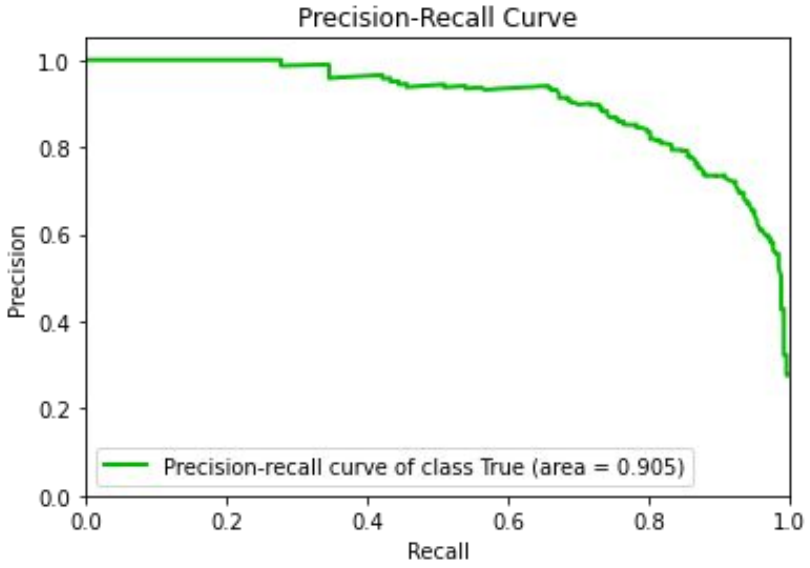
criterion: función de medida de calidad del corte

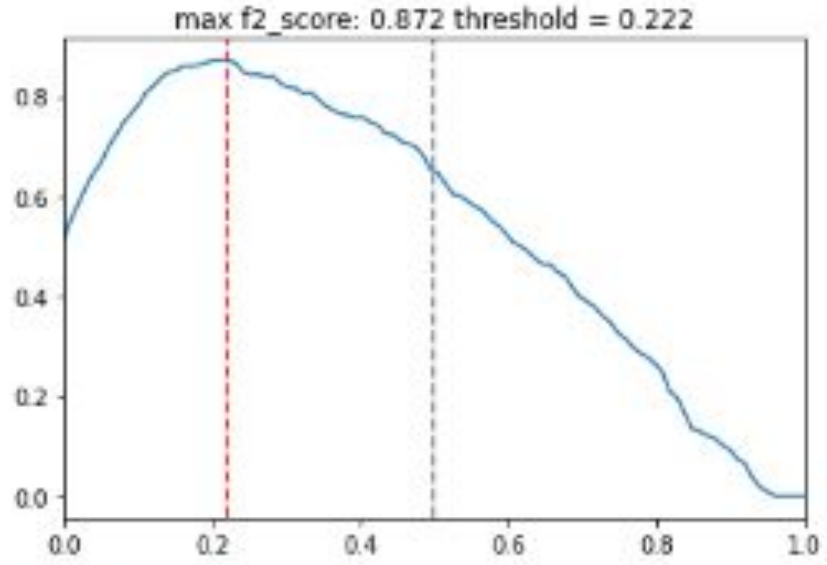
class_weight: balanced

```
parameters = {
    "class_weight":["balanced"],
    'max_depth':[25, 40, 2],
    'criterion' : ["gini", "entropy"]
       }
```

```
gridsearch4.best_params_
```

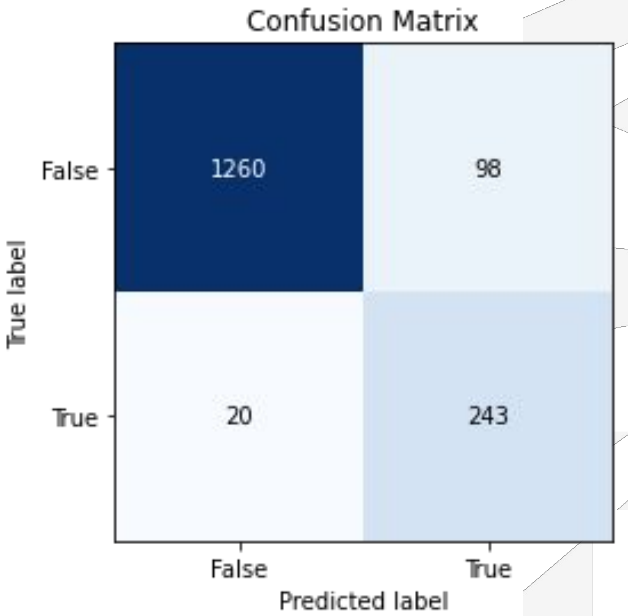
```
{'class_weight': 'balanced', 'criterion': 'entropy', 'max_depth': 25}
```






```
### threshold = 0.222
accuracy: 0.927
f2: 0.872
AUPRC: 0.905
### threshold = 0.500
accuracy: 0.930
f2: 0.654
AUPRC: 0.905
```

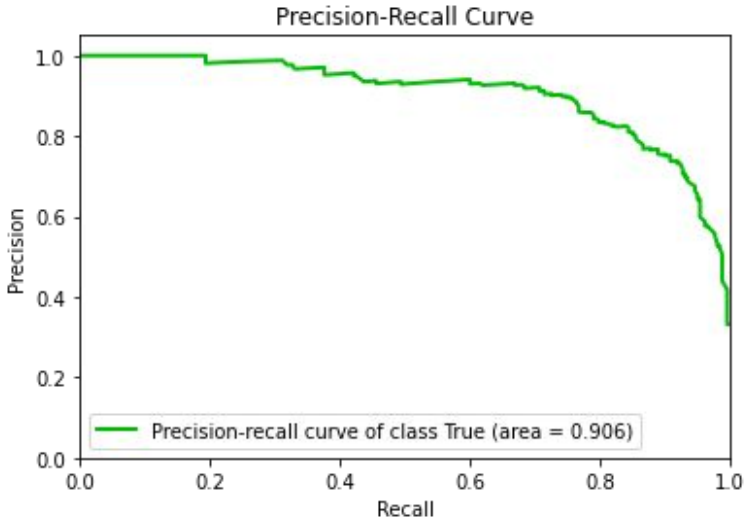
```
precision = 0.7126
recall = 0.9240
f1 = 0.8046
```

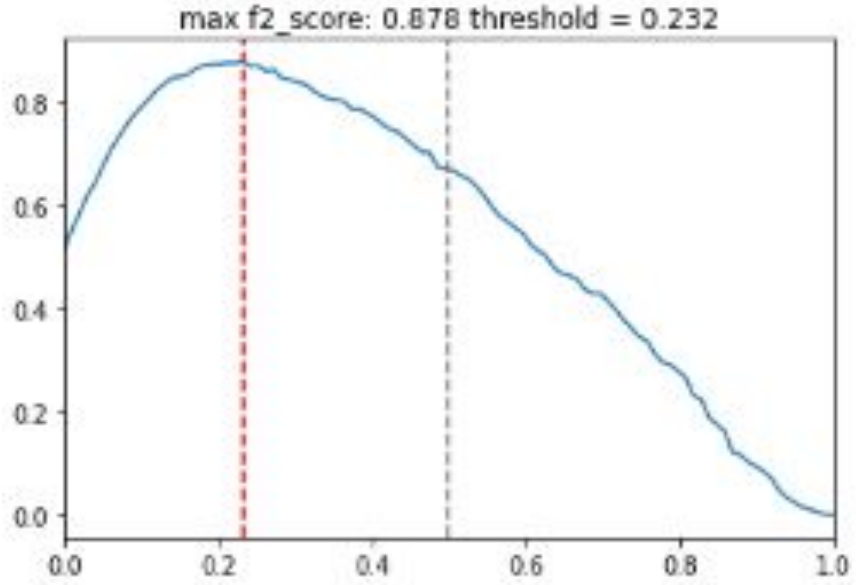


	params	AUPRC	EXT__class_weight	EXT__criterion	EXT__max_depth
4	{'EXT__class_weight': 'balanced', 'EXT__criter...	0.907509	balanced	entropy	40
0	{'EXT__class_weight': 'balanced', 'EXT__criter...	0.901658	balanced	gini	25
1	{'EXT__class_weight': 'balanced', 'EXT__criter...	0.900429	balanced	gini	40
3	{'EXT__class_weight': 'balanced', 'EXT__criter...	0.898103	balanced	entropy	25
2	{'EXT__class_weight': 'balanced', 'EXT__criter...	0.711208	balanced	gini	2
5	{'EXT__class_weight': 'balanced', 'EXT__criter...	0.684194	balanced	entropy	2

	feature	importance
16	Total_Trans_Ct	0.1713
15	Total_Trans_Amt	0.1259
12	Total_Revolving_Bal	0.1048
17	Total_Ct_Chng_Q4_Q1	0.0735
8	Total_Relationship_Count	0.0598
14	Total_Amt_Chng_Q4_Q1	0.0489
18	Avg_Utilization_Ratio	0.0482
9	Months_Inactive_12_mon	0.0419
10	Contacts_Count_12_mon	0.0400
11	Credit_Limit	0.0341
13	Avg_Open_To_Buy	0.0312
0	Customer_Age	0.0311
7	Months_on_book	0.0303
2	Dependent_count	0.0278
3	Education_Level	0.0265
5	Income_Category	0.0257
4	Marital_Status	0.0235
1	Gender	0.0192
29	Total_Trans_Amt_right	0.0113
24	Contacts_Count_12_mon_right	0.0086
6	Card_Category	0.0082
28	Total_Amt_Chng_Q4_Q1_right	0.0040
31	Total_Ct_Chng_Q4_Q1_right	0.0021
23	Months_Inactive_12_mon_right	0.0021
30	Total_Trans_Ct_right	0.0000
19	Customer_Age_right	0.0000
27	Avg_Open_To_Buy_right	0.0000
22	Total_Relationship_Count_right	0.0000
26	Total_Revolving_Bal_right	0.0000
25	Credit_Limit_right	0.0000
21	Months_on_book_right	0.0000
20	Dependent_count_right	0.0000
32	Avg_Utilization_Ratio_right	0.0000

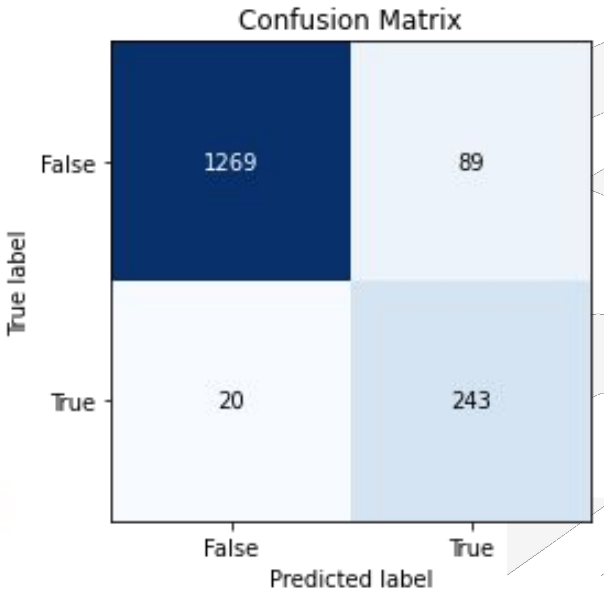
1. Valores bajos
2. Si tiene sentido para el problema
3. No cambia el resultado para peor






```
### threshold = 0.232
accuracy: 0.933
F2: 0.878
AUPRC: 0.906
### threshold = 0.500
accuracy: 0.932
F2: 0.671
AUPRC: 0.906
```

```
precision = 0.7319
recall = 0.9240
f1 = 0.8168
```



Random Forest Classifier

n_estimators: número de árboles

RFC__max_features: número de variables a considerar cuando se hace el mejor corte

RFC__max_depth: número máximo de profundidad del árbol

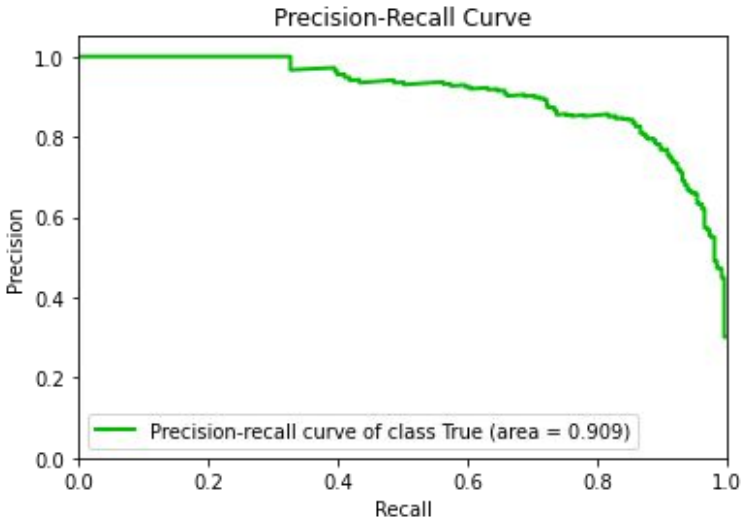
RFC__criterion: función de medida de calidad del corte

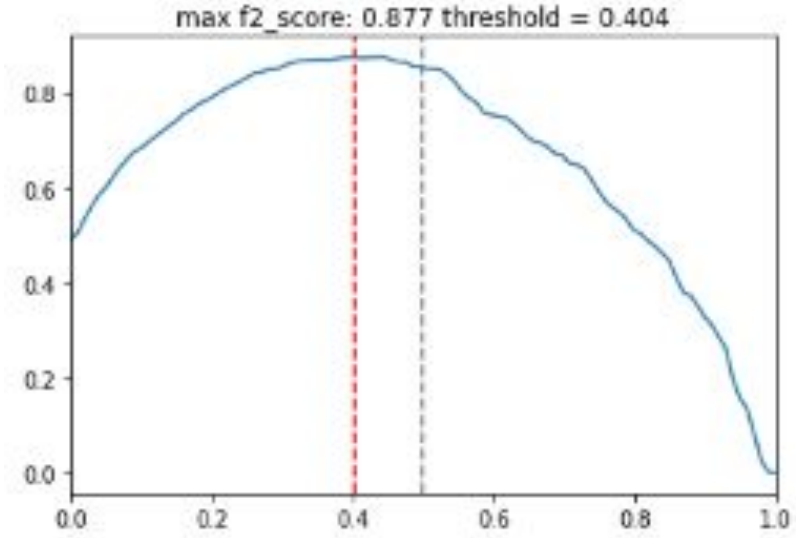
class_weight:"balanced"

```
param_gridRFC={
    'RFC__n_estimators': [200, 500],
    'RFC__max_features': ['auto', 'sqrt'],
    'RFC__max_depth' : [2, 5, 9],
    'RFC__criterion' :['gini', 'entropy']
}
```

```
gridsearch2.best_params_
```

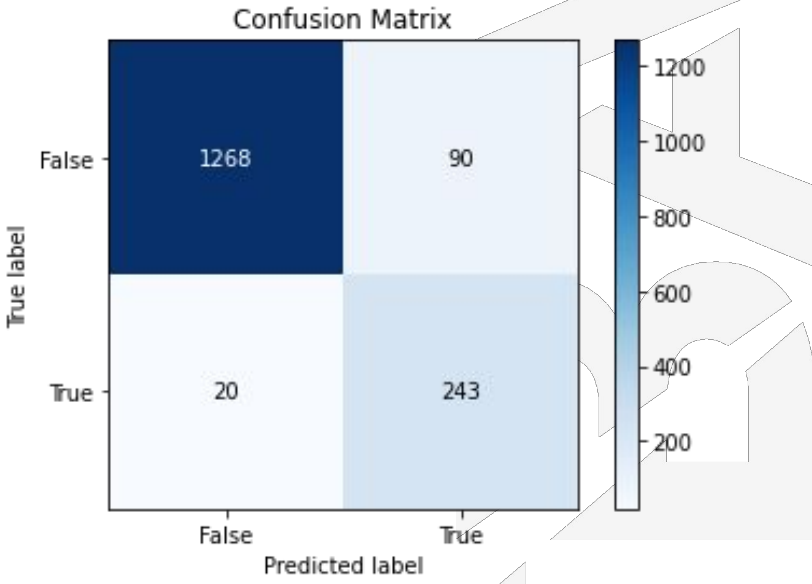
```
{'criterion': 'entropy',
 'max_depth': 9,
 'max_features': 'log2',
 'n_estimators': 500}
```






```
### threshold = 0.404
accuracy: 0.932
f2: 0.877
AUPRC: 0.909
### threshold = 0.500
accuracy: 0.948
f2: 0.855
AUPRC: 0.909
```

```
precision = 0.7297
recall = 0.9240
f1 = 0.8154
```

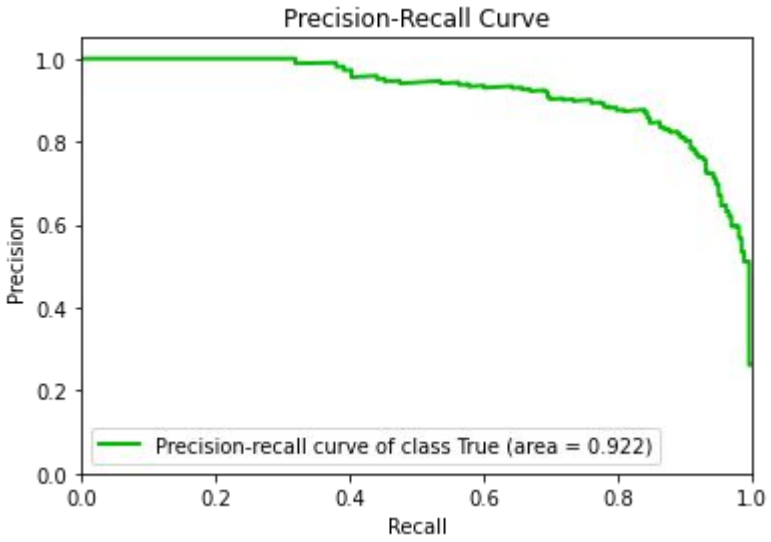


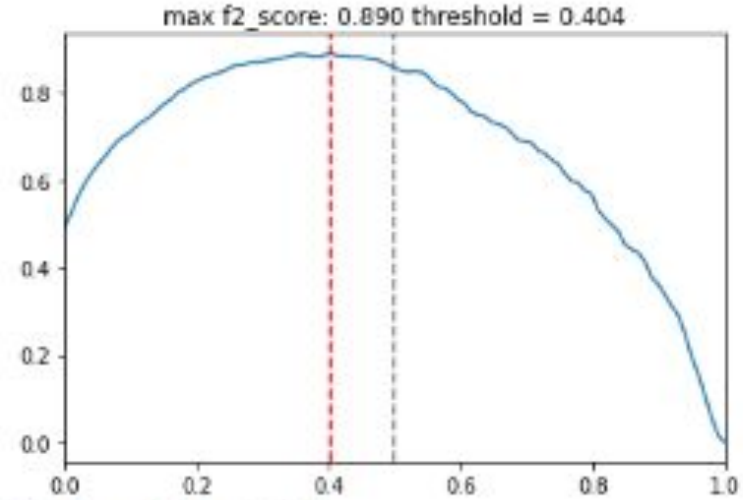
	params	AUPRC	RFC__criterion	RFC__max_depth	RFC__max_features	RFC__n_estimators
22	{'RFC__criterion': 'entropy', 'RFC__max_depth'...	0.9204	entropy	9	sqrt	200
21	{'RFC__criterion': 'entropy', 'RFC__max_depth'...	0.9189	entropy	9	log2	500
23	{'RFC__criterion': 'entropy', 'RFC__max_depth'...	0.9172	entropy	9	sqrt	500
11	{'RFC__criterion': 'gini', 'RFC__max_depth': 9...	0.9168	gini	9	sqrt	500
9	{'RFC__criterion': 'gini', 'RFC__max_depth': 9...	0.9164	gini	9	log2	500
20	{'RFC__criterion': 'entropy', 'RFC__max_depth'...	0.9162	entropy	9	log2	200

Feature importance

1. Valores bajos
2. Si tiene sentido para el problema
3. No cambia el resultado para peor

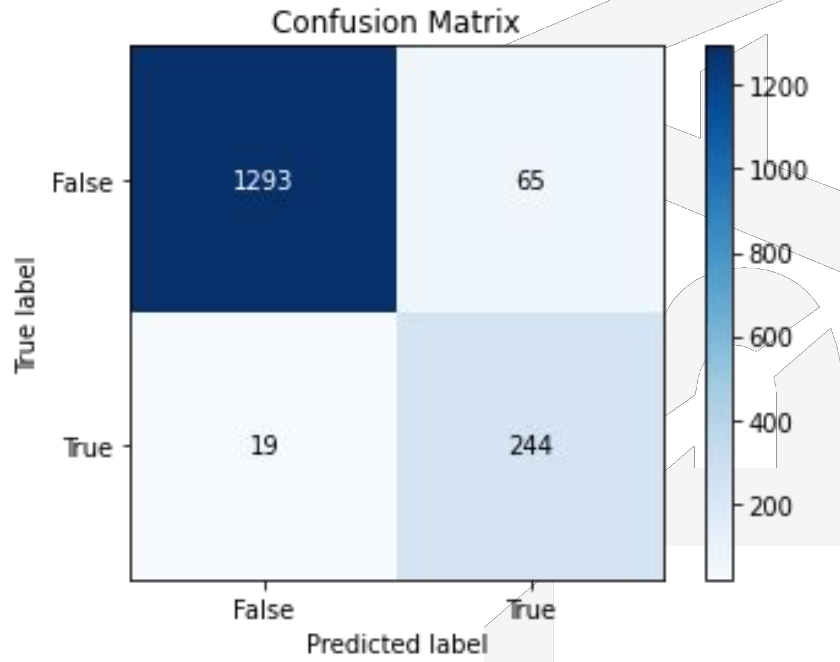
	feature	importance
15	Total_Trans_Amt	0.2150
16	Total_Trans_Ct	0.2088
12	Total_Revolving_Bal	0.1027
17	Total_Ct_Chng_Q4_Q1	0.1010
18	Avg_Utilization_Ratio	0.0676
14	Total_Amt_Chng_Q4_Q1	0.0603
8	Total_Relationship_Count	0.0457
13	Avg_Open_To_Buy	0.0302
11	Credit_Limit	0.0295
9	Months_Inactive_12_mon	0.0294
10	Contacts_Count_12_mon	0.0230
0	Customer_Age	0.0214
7	Months_on_book	0.0168
1	Gender	0.0073
29	Total_Trans_Amt_right	0.0068
2	Dependent_count	0.0066
5	Income_Category	0.0065
3	Education_Level	0.0056
4	Marital_Status	0.0052
24	Contacts_Count_12_mon_right	0.0047
28	Total_Amt_Chng_Q4_Q1_right	0.0028
6	Card_Category	0.0021
31	Total_Ct_Chng_Q4_Q1_right	0.0009
23	Months_Inactive_12_mon_right	0.0003
19	Customer_Age_right	0.0000
30	Total_Trans_Ct_right	0.0000
27	Avg_Open_To_Buy_right	0.0000
22	Total_Relationship_Count_right	0.0000
26	Total_Revolving_Bal_right	0.0000
25	Credit_Limit_right	0.0000
21	Months_on_book_right	0.0000
20	Dependent_count_right	0.0000
32	Avg_Utilization_Ratio_right	0.0000





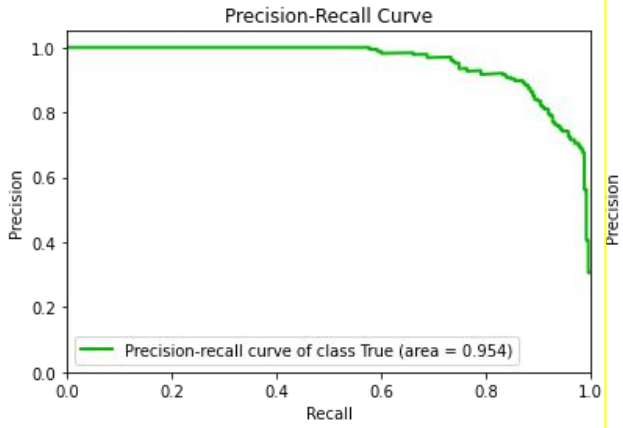

```
### threshold = 0.404
accuracy: 0.940
f2: 0.890
AUPRC: 0.922
### threshold = 0.500
accuracy: 0.952
f2: 0.859
AUPRC: 0.922
```

```
precision = 0.7562
recall = 0.9316
f1 = 0.8348
```



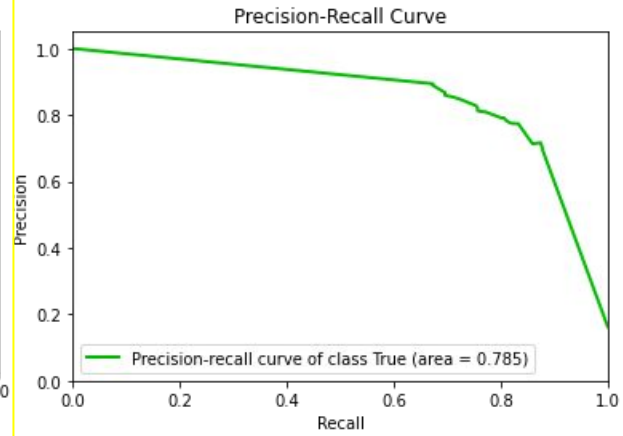
Comparamos modelos

LGBMClassifier



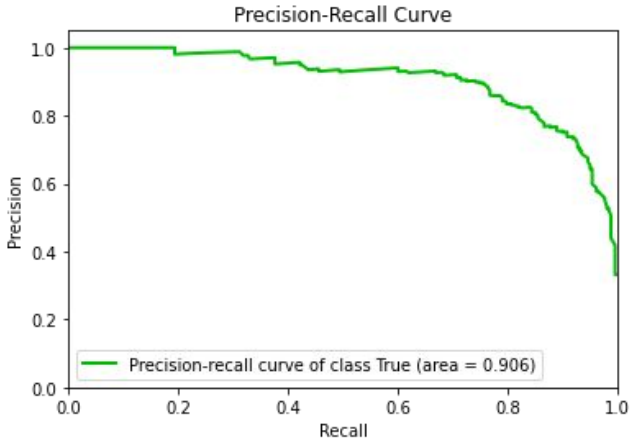
precision = 0.7060
recall = 0.9772
f1 = 0.8198

Decision Tree Classifier



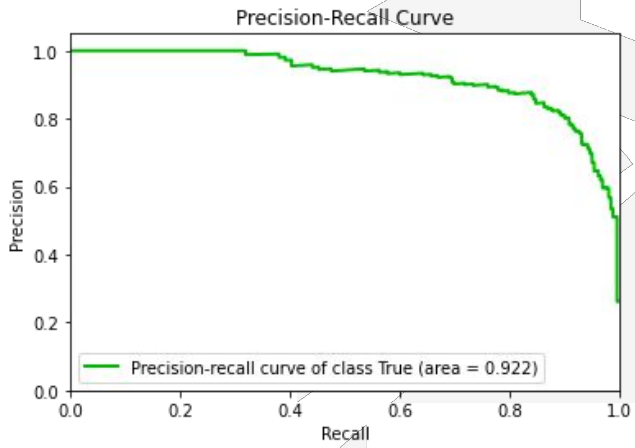
precision = 0.7165
recall = 0.8745
f1 = 0.7877

Extra Trees Classifier



precision = 0.7319
recall = 0.9240
f1 = 0.8168

Random Forest Classifier



precision = 0.7562
recall = 0.9316
f1 = 0.8348

Conclusión

Card category: blue
Marital status: married / single
Months inactive 12 mon: 2 / 3
Gender: M / F
Education level: High school / graduate

Total trans amt: 0-3000
Total trans ct: 0-1000

Less than $40K
Dependent count: 2 / 3
Total relationship count: 2 / 3
Contact count: 2 / 3 / 4

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Contacts_Count_12_mon	Credit_Limit
9616	751155783	Existing Customer	47	F	2	High School	Married	$40K - $60K	Blue	40	2	1	3	4074.0000
7865	714998508	Existing Customer	53	M	3	Uneducated	Married	$120K +	Blue	36	2	2	0	3742.0000
73	820582308	Existing Customer	42	M	5	Uneducated	Married	$80K - $120K	Blue	37	6	2	2	22913.0000
596	720370533	Attrited Customer	55	M	3	Uneducated	Married	$60K - $80K	Blue	44	3	2	2	2323.0000
114	711844758	Existing Customer	48	M	3	Graduate	Single	$80K - $120K	Blue	35	6	1	0	13551.0000

Total_Revolving_Bal	Avg_Open_To_Buy	Total_Amt_Chng_Q4_Q1	Total_Trans_Amt	Total_Trans_Ct	Total_Ct_Chng_Q4_Q1	Avg_Utilization_Ratio
1868	2206.0000	0.6880	15005	118	0.7610	0.4590
1454	2288.0000	0.8940	5326	62	0.6760	0.3890
1528	21385.0000	0.4140	1394	35	0.5220	0.0670
0	2323.0000	0.7370	804	15	0.5000	0.0000
1294	12257.0000	0.7910	1388	37	1.0560	0.0950

CLIENTNUM	Attrition_Flag
751155783	False
714998508	False
820582308	False
720370533	True
711844758	False

ITBA
Instituto Tecnológicc
de Buenos Aires

MUCHAS GRACIAS