LABORATORIO 17

In [49]:
```
#Just in Case
import warnings
warnings.filterwarnings('ignore')

#Importando las librerías necesarias
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import statsmodels.api as sm


from graphviz import Source
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier, export_graphviz, export_text, plot_tree
from imblearn.under_sampling import RandomUnderSampler #Para llevar a cabo UnderSampling
from sklearn.metrics import confusion_matrix, auc, roc_curve
from sklearn.preprocessing import label_binarize
from mlxtend.plotting import plot_decision_regions
```

In [50]:
```
#Estableciendo el directorio de trabajo
os.chdir('D:\Social Data Consulting\Python for Data Science\data')
```

In [51]:
```
mifichero="UCI_Credit_Card.csv"
creditcard=pd.read_csv(mifichero)
creditcard.head()
```

Out[51]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BIL
0	1	20000.0	2	2	1	24	2	2	-1	-1	...	0.0	0.0	
1	2	120000.0	2	2	2	26	-1	2	0	0	...	3272.0	3455.0	
2	3	90000.0	2	2	2	34	0	0	0	0	...	14331.0	14948.0	
3	4	50000.0	2	2	1	37	0	0	0	0	...	28314.0	28959.0	
4	5	50000.0	1	2	1	57	-1	0	-1	0	...	20940.0	19146.0	

5 rows × 25 columns

In [52]:
```
creditcard.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   ID                          30000 non-null  int64  
 1   LIMIT_BAL                   30000 non-null  float64
 2   SEX                         30000 non-null  int64  
 3   EDUCATION                   30000 non-null  int64  
 4   MARRIAGE                    30000 non-null  int64  
 5   AGE                         30000 non-null  int64  
 6   PAY_0                       30000 non-null  int64  
 7   PAY_2                       30000 non-null  int64  
 8   PAY_3                       30000 non-null  int64  
 9   PAY_4                       30000 non-null  int64  
 10  PAY_5                       30000 non-null  int64  
 11  PAY_6                       30000 non-null  int64  
 12  BILL_AMT1                   30000 non-null  float64
 13  BILL_AMT2                   30000 non-null  float64
 14  BILL_AMT3                   30000 non-null  float64
 15  BILL_AMT4                   30000 non-null  float64
 16  BILL_AMT5                   30000 non-null  float64
 17  BILL_AMT6                   30000 non-null  float64
 18  PAY_AMT1                    30000 non-null  float64
 19  PAY_AMT2                    30000 non-null  float64
 20  PAY_AMT3                    30000 non-null  float64
 21  PAY_AMT4                    30000 non-null  float64
 22  PAY_AMT5                    30000 non-null  float64
 23  PAY_AMT6                    30000 non-null  float64
 24  default.payment.next.month  30000 non-null  int64  
dtypes: float64(13), int64(12)
memory usage: 5.7 MB
```

In [53]:
```
creditcard.isnull().sum()
```

Out[53]:
```
ID                            0
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default.payment.next.month    0
dtype: int64
```

In [54]:
```
pd.value_counts(creditcard['default.payment.next.month'])
```
Out[54]:
```
0    23364
1     6636
Name: default.payment.next.month, dtype: int64
```

In [55]:
```
predictores=['LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0', 'PAY_2',
       'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']
target=['default.payment.next.month']
```

In [56]:
```
del creditcard['ID']
```

1. Construir data de entrenamiento y testeo

In [57]:
```
creditcard.shape[1]
```
Out[57]: 24

In [58]:
```
X=creditcard.iloc[:,0:creditcard.shape[1]-1].values
y=creditcard.iloc[:,creditcard.shape[1]-1].values
```

In [59]:
```
xtrain,xtest,ytrain,ytest=train_test_split(X,
                                           y,
                                           test_size=0.2,
                                           random_state=2020,
                                           stratify=y)
```

In [60]:
```
#Datos de entrenamiento
df_xtrain= pd.DataFrame(xtrain,columns=predictores)
df_ytrain= pd.DataFrame(ytrain,columns=target)

df_creditcard_entrenamiento = pd.concat([df_xtrain,df_ytrain], axis=1)
df_creditcard_entrenamiento.head()
```

Out[60]:

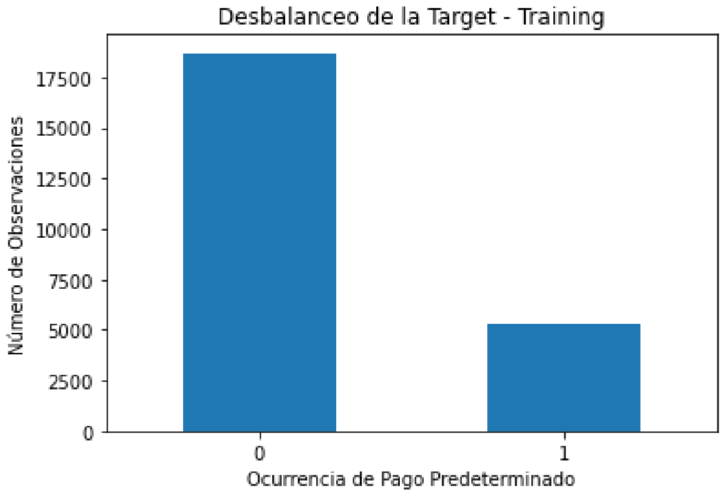
	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT4	BILL_AMT5
0	110000.0	1.0	2.0	1.0	36.0	1.0	2.0	0.0	0.0	0.0	...	105373.0	71733.0
1	50000.0	2.0	2.0	2.0	26.0	-1.0	-1.0	-1.0	-1.0	-2.0	...	0.0	0.0
2	140000.0	2.0	2.0	2.0	49.0	-2.0	-2.0	-2.0	-2.0	-2.0	...	3794.0	0.0
3	50000.0	1.0	3.0	1.0	47.0	0.0	0.0	0.0	2.0	0.0	...	15181.0	15928.0
4	20000.0	1.0	2.0	2.0	43.0	-1.0	-1.0	-1.0	-1.0	-1.0	...	54.0	54.0

5 rows × 24 columns

2. Utilizar UnderSampling para balanceo de datos, teniendo en cuenta los siguientes parámetros: 07 para proporción de etiquetas poco representadas y 2020 como semilla.

In [61]:
```
count_classes=pd.value_counts(df_creditcard_entrenamiento['default.payment.next.month'])
count_classes
```
Out[61]:
```
0    18691
1     5309
Name: default.payment.next.month, dtype: int64
```

In [62]:
```
#Graficando el Desbalanceo de la Target en el Training Set
count_classes.plot(kind='bar',rot=0)
plt.title('Desbalanceo de la Target - Training')
plt.xlabel('Ocurrencia de Pago Predeterminado')
plt.ylabel('Número de Observaciones')
plt.show()
```



In [63]:
```
#Primero creamos una instancia de NearMiss
us=RandomUnderSampler(sampling_strategy=0.7,random_state=2020)
```

In [64]:
```
#fit_resample me arroja 2 objetos ya balanceados
xtrain_under,ytrain_under= us.fit_resample(xtrain,ytrain)
```

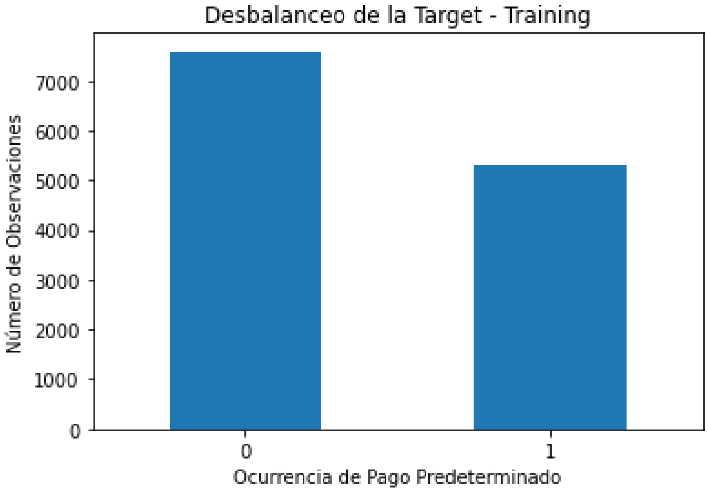
In [65]:
```
#Datos de Entrenamiento DF
xtrain_under_df=pd.DataFrame(xtrain_under,columns=predictores)
ytrain_under_df=pd.DataFrame(ytrain_under,columns=target)

xtest_df=pd.DataFrame(xtest,columns=predictores)
ytest_df=pd.DataFrame(ytest,columns=target)


df_creditcard_entrenamiento=pd.concat([xtrain_under_df,ytrain_under_df],axis=1)
df_creditcard_test=pd.concat([xtest_df,ytest_df],axis=1)
df_creditcard_entrenamiento.head()
```

Out[65]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT4	BILL_AMT5
0	30000.0	1.0	3.0	1.0	59.0	0.0	0.0	0.0	0.0	0.0	...	21624.0	21833.0
1	50000.0	1.0	3.0	2.0	26.0	0.0	0.0	0.0	0.0	0.0	...	20284.0	19166.0
2	360000.0	2.0	2.0	2.0	33.0	-1.0	-1.0	-1.0	-1.0	0.0	...	4912.0	1150.0
3	340000.0	2.0	2.0	2.0	43.0	0.0	0.0	2.0	0.0	0.0	...	114379.0	113627.0
4	450000.0	1.0	1.0	2.0	28.0	-1.0	0.0	0.0	0.0	-1.0	...	19585.0	9756.0

5 rows × 24 columns

In [66]:
```
count_classes=pd.value_counts(df_creditcard_entrenamiento['default.payment.next.month'])
#Graficando el Desbalanceo de la Target en el Training Set balanceado
count_classes.plot(kind='bar',rot=0)
plt.title('Desbalanceo de la Target - Training')
plt.xlabel('Ocurrencia de Pago Predeterminado')
plt.ylabel('Número de Observaciones')
plt.show()
```



3. Construir el modelo de árboles de decisión

In [67]:
```
#Creacion del modelo de arbol de decision
tree=DecisionTreeClassifier(criterion='entropy',
                            min_samples_split=20,
                            max_depth=3,
                            random_state=2020)
```

In [68]:
```
#Evaluando la validacion cruzada
score=cross_val_score(tree, # Estimator
                      xtrain_under, #Matriz de Datos
                      ytrain_under, #Target
                      scoring='accuracy', #Metrica de referencia
                      cv=10) #Numero de particiones
score
```

Out[68]:
```
array([0.72635659, 0.73643411, 0.7255814 , 0.72924748, 0.71605896,
       0.71916214, 0.72148953, 0.70752521, 0.72692009, 0.71761055])
```

In [69]:
```
#Aprendemos de los datos de entrenamiento
tree=tree.fit(xtrain_under,ytrain_under)
```

4. Graficar el árbol de decisión.

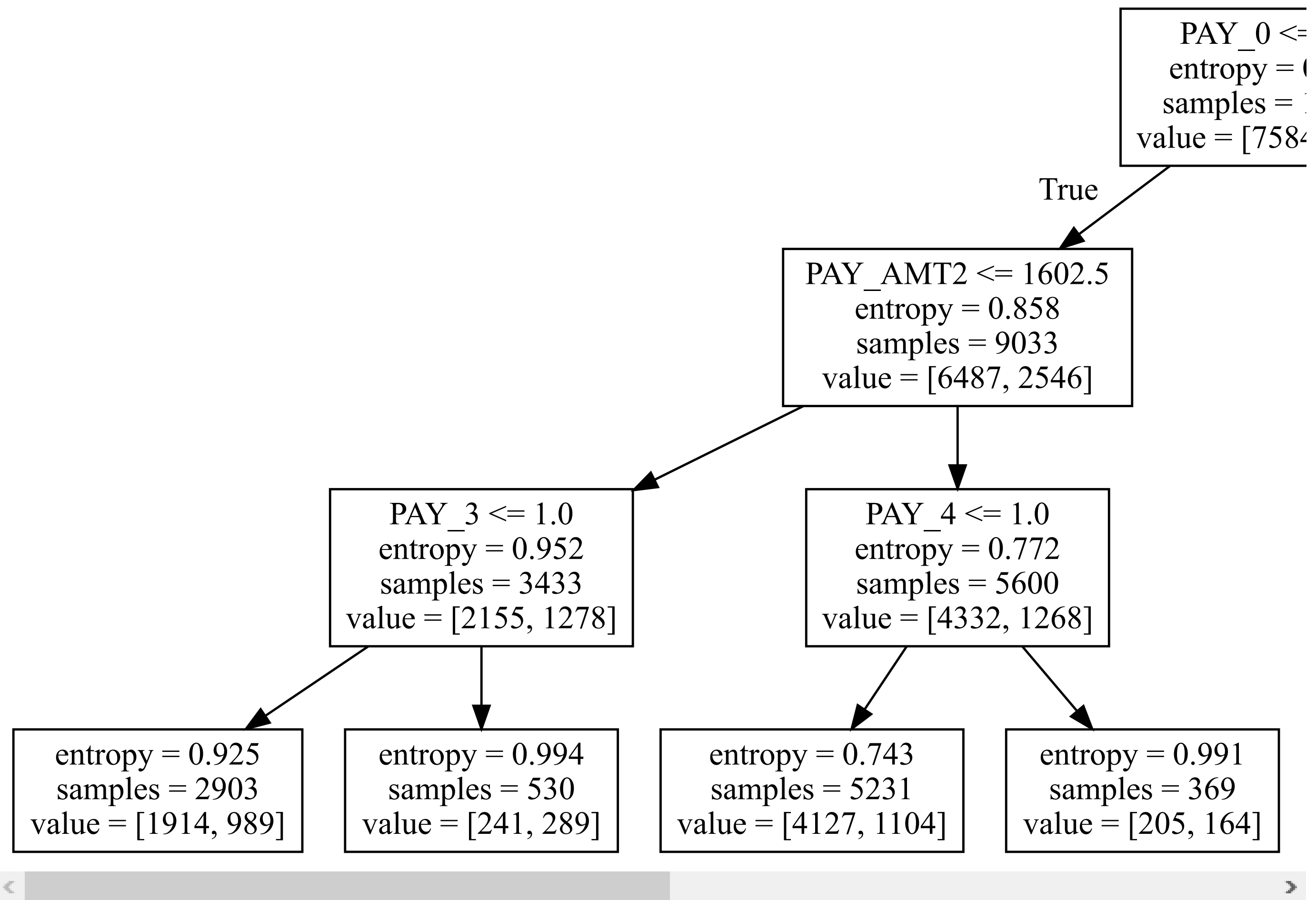
In [70]:
```
#Iniciando proceso de grafica
with open('creditcard_dtree.dot','w') as dotfile : #W viene de write para escritura sobre el objet
    export_graphviz(tree,
                    out_file=dotfile,
                    feature_names=predictores)
    dotfile.close()
```

In [71]:
```
#Leyendo el archivo creado
file=open('creditcard_dtree.dot','r') #r viene de read
text=file.read()
text
```

Out[71]:
```
'digraph Tree {\nnode [shape=box] ;\n0 [label="PAY_0 <= 0.5\\nentropy = 0.977\\nsamples = 12893
\\nvalue = [7584, 5309]"] ;\n1 [label="PAY_AMT2 <= 1602.5\\nentropy = 0.858\\nsamples = 9033\\nv
alue = [6487, 2546]"] ;\n0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"] ;\n2 [label
="PAY_3 <= 1.0\\nentropy = 0.952\\nsamples = 3433\\nvalue = [2155, 1278]"] ;\n1 -> 2 ;\n3 [label
="entropy = 0.925\\nsamples = 2903\\nvalue = [1914, 989]"] ;\n2 -> 3 ;\n4 [label="entropy = 0.99
4\\nsamples = 530\\nvalue = [241, 289]"] ;\n2 -> 4 ;\n5 [label="PAY_4 <= 1.0\\nentropy = 0.772
\\nsamples = 5600\\nvalue = [4332, 1268]"] ;\n1 -> 5 ;\n6 [label="entropy = 0.743\\nsamples = 52
31\\nvalue = [4127, 1104]"] ;\n5 -> 6 ;\n7 [label="entropy = 0.991\\nsamples = 369\\nvalue = [20
5, 164]"] ;\n5 -> 7 ;\n8 [label="PAY_0 <= 1.5\\nentropy = 0.861\\nsamples = 3860\\nvalue = [109
7, 2763]"] ;\n0 -> 8 [labeldistance=2.5, labelangle=-45, headlabel="False"] ;\n9 [label="PAY_5 <
= 1.0\\nentropy = 0.991\\nsamples = 1777\\nvalue = [787, 990]"] ;\n8 -> 9 ;\n10 [label="entropy
= 1.0\\nsamples = 1380\\nvalue = [672, 708]"] ;\n9 -> 10 ;\n11 [label="entropy = 0.868\\nsamples
= 397\\nvalue = [115, 282]"] ;\n9 -> 11 ;\n12 [label="PAY_3 <= -0.5\\nentropy = 0.607\\nsamples
= 2083\\nvalue = [310, 1773]"] ;\n8 -> 12 ;\n13 [label="entropy = 0.895\\nsamples = 106\\nvalue
= [33, 73]"] ;\n12 -> 13 ;\n14 [label="entropy = 0.585\\nsamples = 1977\\nvalue = [277, 1700]"]
;\n12 -> 14 ;\n}'
```

In [72]:
```
#Visualizando el grafico de arbol
Source(text)
```

Out[72]:



5. Generar las gráficas de variables importantes.

In [73]:
```
tree.feature_importances_
```

Out[73]:
```
array([0.        , 0.        , 0.        , 0.        , 0.        ,
       0.84644316, 0.        , 0.03232047, 0.03095561, 0.01676595,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.0735148 , 0.        ,
       0.        , 0.        , 0.        ])
```

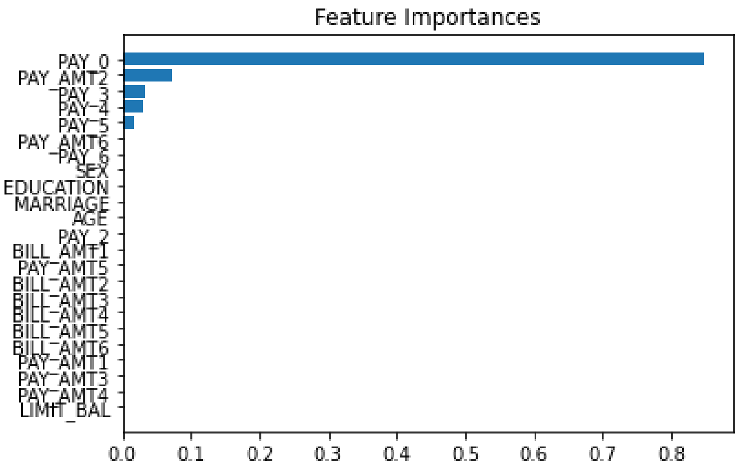
In [74]:
```
importancia_predictores = pd.DataFrame(
                            {'predictor': df_creditcard_entrenamiento.drop(columns ='default.payme
                             'importancia': tree.feature_importances_}
                            )
print("Importancia de los predictores en el modelo")
print("-------------------------------------------")
importancia_predictores.sort_values('importancia', ascending=False)
```

```
Importancia de los predictores en el modelo
-------------------------------------------
```

Out[74]:

	predictor	importancia
5	PAY_0	0.846443
18	PAY_AMT2	0.073515
7	PAY_3	0.032320
8	PAY_4	0.030956
9	PAY_5	0.016766
0	LIMIT_BAL	0.000000
14	BILL_AMT4	0.000000
21	PAY_AMT5	0.000000
20	PAY_AMT4	0.000000
19	PAY_AMT3	0.000000
17	PAY_AMT1	0.000000
16	BILL_AMT6	0.000000
15	BILL_AMT5	0.000000
11	BILL_AMT1	0.000000
13	BILL_AMT3	0.000000
12	BILL_AMT2	0.000000
1	SEX	0.000000
10	PAY_6	0.000000
6	PAY_2	0.000000
4	AGE	0.000000
3	MARRIAGE	0.000000
2	EDUCATION	0.000000
22	PAY_AMT6	0.000000

In [75]:
```
plt.title('Feature Importances')
plt.barh(importancia_predictores.sort_values('importancia', ascending=True).predictor,importancia_
plt.show()
```



6. Métricas de evaluación de modelos para datos de entrenamiento y testeo

In [76]:
```
prob_train=tree.predict_proba(xtrain_under)
prob_df_train_tree=pd.DataFrame(prob_train[:,1],columns=['prob y=0'])
```

In [77]:
```
punto_corte=0.5
prob_df_train_tree['prediccion']=np.where(prob_df_train_tree['prob y=0']>punto_corte,0,1)
prob_df_train_tree
```

Out[77]:

	prob y=0	prediccion
0	0.340682	1
1	0.211050	1
2	0.211050	1
3	0.545283	0
4	0.211050	1
...	...	...
12888	0.859889	0
12889	0.545283	0
12890	0.513043	0
12891	0.710327	0
12892	0.859889	0

In [78]:
```
prob_test=tree.predict_proba(xtest)
prob_df_test_tree=pd.DataFrame(prob_test[:,1],columns=['prob y=0'])
```

In [79]:
```
punto_corte=0.5
prob_df_test_tree['prediccion']=np.where(prob_df_test_tree['prob y=0']>punto_corte,0,1)
prob_df_test_tree
```

Out[79]:

	prob y=0	prediccion
0	0.340682	1
1	0.211050	1
2	0.211050	1
3	0.545283	0
4	0.211050	1
...	...	...
5995	0.710327	0
5996	0.513043	0
5997	0.859889	0
5998	0.513043	0
5999	0.513043	0

6000 rows × 2 columns

METRICAS PARA DATA DE ENTRENAMIENTO

In [80]:
```
cm_train=pd.crosstab(ytrain_under,prob_df_train_tree['prediccion'])
cm_train
```

Out[80]:

prediccion	**0**	**1**
row_0		
0	1338	6246
1	3052	2257

In [81]:
```
VP_train=cm_train[0][0]
VN_train=cm_train[1][1]
FP_train=cm_train[1][0]
FN_train=cm_train[0][1]
```

In [82]:
```
accuracy_train_tree=(VP_train+VN_train)/(VP_train+VN_train+FP_train+FN_train)
print('El accuracy para la Data de Entrenamiento es: ', accuracy_train_tree.round(3))
```

```
El accuracy para la Data de Entrenamiento es:  0.279
```

In [83]:
```
sensibilidad_train_tree=(VP_train)/(VP_train+FN_train)
print('La sensibilidad para la Data de Entrenamiento es: ', sensibilidad_train_tree.round(3))
```

```
La sensibilidad para la Data de Entrenamiento es:  0.305
```

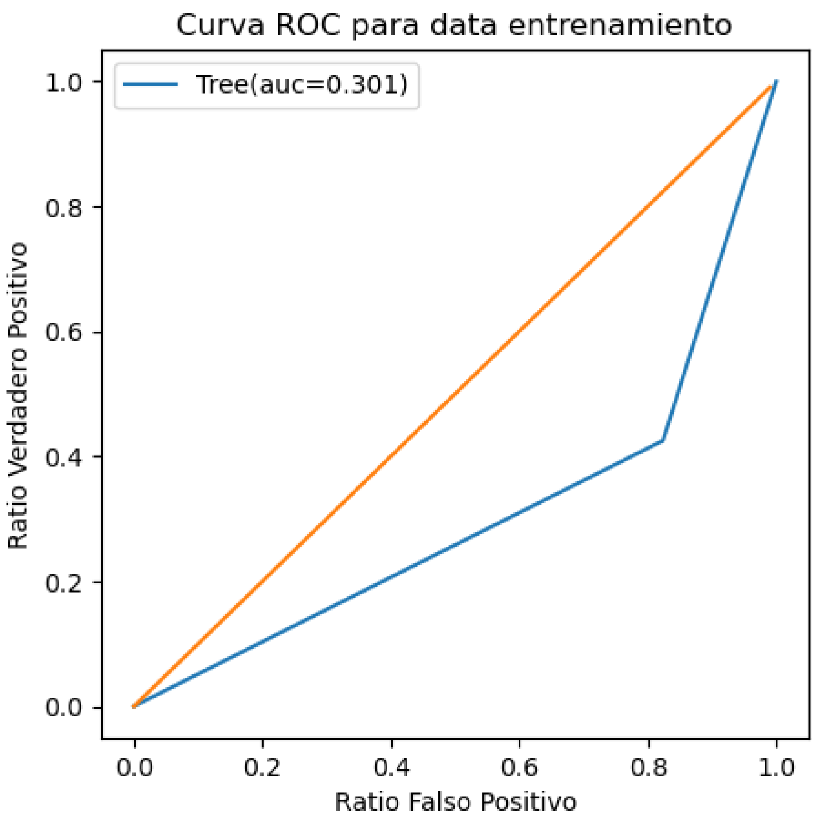
In [84]:
```
especificidad_train_tree=(VN_train)/(VN_train+FP_train)
print('La especificidad para la Data de Entrenamiento es: ', especificidad_train_tree.round(3))
```

```
La especificidad para la Data de Entrenamiento es:  0.265
```

In [85]:
```
#Para calcular de la curva ROC y AUC, la función roc_curve exige que las categorias sean 0 y 1
fpr,tpr,thresholds=roc_curve(ytrain_under,prob_df_train_tree['prediccion'])
auc_train_tree=auc(fpr,tpr)
print('El area Bajo la Curva(AUC) para Data de Entrenamiento es: ',auc_train_tree.round(3))
```

```
El area Bajo la Curva(AUC) para Data de Entrenamiento es:  0.301
```

In [86]:
```
plt.figure(figsize=(5,5),dpi=100)
plt.plot(fpr,tpr,linestyle='-',label="Tree(auc=%0.3f)"%auc_train_tree)
plt.title('Curva ROC para data entrenamiento')
plt.xlabel('Ratio Falso Positivo')
plt.ylabel('Ratio Verdadero Positivo')
plt.legend()

x=[i*0.01 for i in range(100)]
y=[i*0.01 for i in range(100)]
plt.plot(x,y)
plt.show()
```



METRICAS PARA DATA DE TESTING

In [87]:
```
cm_test=pd.crosstab(ytest,prob_df_test_tree['prediccion'])
cm_test
```

Out[87]:

prediccion	0	1
row_0		
0	859	3814
1	736	591

In [88]:
```
VP_test=cm_test[0][0]
VN_test=cm_test[1][1]
FP_test=cm_test[1][0]
FN_test=cm_test[0][1]
```

In [89]:
```python
accuracy_test_tree=(VP_test+VN_test)/(VP_test+VN_test+FP_test+FN_test)
print('El accuracy para la Data de Testeo es: ', accuracy_test_tree.round(3))
```

```
El accuracy para la Data de Testeo es:  0.242
```

In [90]:
```python
sensibilidad_test_tree=(VP_test)/(VP_test+FN_test)
print('La sensibilidad para la Data de Testeo es: ', sensibilidad_test_tree.round(3))
```

```
La sensibilidad para la Data de Testeo es:  0.539
```

In [91]:
```python
especificidad_test_tree=(VN_test)/(VN_test+FP_test)
print('La especificidad para la Data de Testeo es: ', especificidad_test_tree.round(3))
```

```
La especificidad para la Data de Testeo es:  0.134
```

In [92]:
```python
#Para calcular de la curva ROC y AUC, la función roc_curve exige que las categorias sean 0 y 1
fpr,tpr,thresholds=roc_curve(ytest,prob_df_test_tree['prediccion'])
auc_test_tree=auc(fpr,tpr)
print('El area Bajo la Curva(AUC) para Data de Entrenamiento es: ',auc_test_tree.round(3))
```

```
El area Bajo la Curva(AUC) para Data de Entrenamiento es:  0.315
```

In [93]:
```python
plt.figure(figsize=(5,5),dpi=100)
plt.plot(fpr,tpr,linestyle='-',label="Tree(auc=%0.3f)"%auc_test_tree)
plt.title('Curva ROC para data testeo')
plt.xlabel('Ratio Falso Positivo')
plt.ylabel('Ratio Verdadero Positivo')
plt.legend()

x=[i*0.01 for i in range(100)]
y=[i*0.01 for i in range(100)]
plt.plot(x,y)
plt.show()
```