DESARROLLO DEL LABORATORIO Nº15

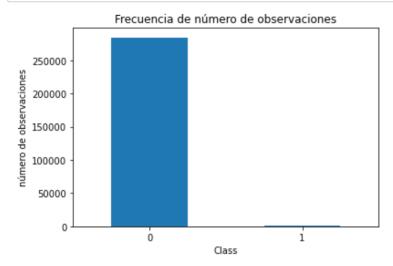
```
In [47]:
         #Importando librerías necesarias
          import os
          import pandas as pd
          import numpy as np
          import seaborn as sns
                                    #Librería Gráfica
          import matplotlib.pyplot as plt #Librería Gráfica
          from sklearn.model selection import train test split
          from imblearn.under sampling import NearMiss
                                                                  #Para llevar a cabo UnderSamplina
          from sklearn.linear_model import LogisticRegression
          from sklearn.feature selection import RFE
          import statsmodels.api as sm #Para Análisis de Regresión Logística con librería stats
          import warnings
          warnings.filterwarnings('ignore')
 In [2]: os.chdir("D:\Social Data Consulting\Python for Data Science\data")
 In [8]:
         miArchivo='creditcard.csv'
          df=pd.read csv(miArchivo, sep=',')
          del df['Time']
 In [9]:
         df.head()
 Out[9]:
                   V1
                            V2
                                     V3
                                              V4
                                                       V5
                                                                 V6
                                                                          V7
                                                                                   V8
                                                                                             V9
                                                                                                     V10 ...
          0 -1.359807 -0.072781 2.536347
                                         1.378155 -0.338321
                                                            0.462388
                                                                     0.239599
                                                                               0.098698
                                                                                        0.363787
                                                                                                 0.090794 ... -0.0183
             1.191857
                       0.266151 0.166480
                                         0.448154
                                                  0.060018
                                                           -0.082361
                                                                     -0.078803
                                                                               0.085102 -0.255425
                                                                                                 -0.166974 ... -0.2257
            -1.358354 -1.340163 1.773209
                                         0.379780
                                                  -0.503198
                                                            1.800499
                                                                     0.791461
                                                                               0.247676 -1.514654
                                                                                                 0.207643 ...
                                                                                                              0.2479
             -0.966272 -0.185226 1.792993
                                         -0.863291 -0.010309
                                                            1.247203
                                                                     0.237609
                                                                               0.377436 -1.387024
                                                                                                 -0.054952 ... -0.1083
             -1.158233 0.877737 1.548718
                                         0.403034 -0.407193
                                                            0.095921
                                                                     0.592941 -0.270533
                                                                                        0.817739
                                                                                                 0.753074 ... -0.0094
          5 rows × 30 columns
          1. Asignar el 60% y 40% a la data de entrenamiento y testeo respectivamente.
         #Dividimos La data (entrenamiento y testeo)
In [16]: X=df.iloc[:,:29]
          y=df.iloc[:,29]
In [17]: X_train,X_test,y_train,y_test=train_test_split(X,
```

2. Crear un dataframe a partir de la data de entrenamiento con la tecnica de balanceo de datos "UnderSampling" y parámetro de balanceo 0.7.

test_size=0.4,
random state=2021,

stratify=y)

```
In [31]: #Visualizamos el desbalanceo
    count_classes = pd.value_counts(df['Class'], sort = True)
    count_classes.plot(kind = 'bar', rot=0)
    #plt.xticks(range(2))
    plt.title("Frecuencia de número de observaciones")
    plt.xlabel("Class")
    plt.ylabel("número de observaciones")
    plt.show()
```



```
In [19]: #fit_resample me arroja 2 objetos ya balanceados
    xtrain_under,ytrain_under= under.fit_resample(X_train,y_train)
```

```
In [23]: #Datos de Entrenamiento DF
    xtrain_under=pd.DataFrame(xtrain_under,columns=columns)
    ytrain_under=pd.DataFrame(ytrain_under,columns=["Class"])

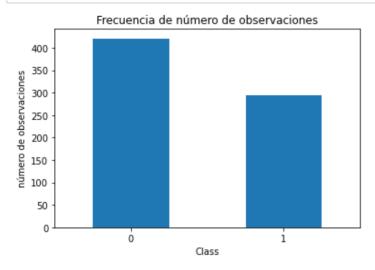
df_entrenamiento_under=pd.concat([xtrain_under,ytrain_under],axis=1)
    df_entrenamiento_under.head()
```

Out[23]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	 V21
0	1.161523	1.173309	-1.602805	1.485067	1.046127	-1.044961	0.568273	-0.078050	-0.649025	-1.413683	 -0.135894
1	1.161685	1.168669	-1.604114	1.485647	1.040086	-1.046640	0.563452	-0.074108	-0.638580	-1.411608	 -0.136753
2	1.146649	1.141946	-1.527127	1.538383	0.900342	-1.174930	0.538144	-0.062330	-0.586083	-1.399037	 -0.128206
3	1.161938	1.193626	-1.596951	1.482299	1.070830	-1.038444	0.586824	-0.093678	-0.690740	-1.421726	 -0.132792
4	1.146760	1.132315	-1.529868	1.539633	0.888153	-1.178248	0.528649	-0.054473	-0.565206	-1.394939	 -0.129857

5 rows × 30 columns

```
In [30]: #Visualizamos el balanceo
    count_classes = pd.value_counts(df_entrenamiento_under['Class'], sort = True)
    count_classes.plot(kind = 'bar', rot=0)
    #plt.xticks(range(2))
    plt.title("Frecuencia de número de observaciones")
    plt.xlabel("Class")
    plt.ylabel("número de observaciones")
    plt.show()
```



3. Utilizar esa data balanceada para aplicar un modelo de regresión logística utilizando sólo 6 variables predictoras (utilice recursive feature elimination (RFE)) y tener en cuenta que el TARGET es Class

```
In [33]: #Instanciamos un objeto de clase LogisticRegression()
logit=LogisticRegression()
```

Aplicando RFE(Recursive Feature Elimination)

```
In [34]: #Numero de variables a quedarse
n=6

In [35]: #Instanciando un objeto RFE
RFE=RFE(estimator=logit,n_features_to_select=n)
```

```
In [38]: #Identificando las variales dentro del modelo
df_vars=df_entrenamiento_under.columns.to_list()
```

```
In [39]: #Detectando Las predictoras y target
    #target
    Y=['Class']
    #predictoras
    X=[v for v in df_vars if v not in Y]
```

```
In [40]: #Aprendiendo de Los datos de entrenamiento
selector=RFE.fit(df_entrenamiento_under[X],df_entrenamiento_under[Y])
```

```
#Mostrar las variables más significativas
In [41]:
          print(selector.support )
          [ True False False False False False False False False False True
           False True True False False False False False False False False
           False False False False]
In [44]: final=zip(df vars, selector.support , selector.ranking )
          list(final)
Out[44]: [('V1', True, 1),
           ('V2', False, 10),
           ('V3', False, 3),
           ('V4', False, 7),
           ('V5', False, 6),
           ('V6', True, 1),
           ('V7', False, 5),
           ('V8', False, 23),
           ('V9', False, 15),
           ('V10', False, 20),
           ('V11', False, 9),
           ('V11', False, 9),

('V12', True, 1),

('V13', False, 18),

('V14', True, 1),

('V15', True, 1),
           ('V16', False, 17),
           ('V17', False, 4),
           ('V18', True, 1),
           ('V19', False, 12),
           ('V20', False, 22),
           ('V21', False, 16),
           ('V22', False, 13),
           ('V23', False, 19),
           ('V24', False, 21),
           ('V25', False, 11),
           ('V26', False, 2),
           ('V27', False, 14),
('V28', False, 24),
           ('Amount', False, 8)]
          Estimación REGRESIÓN LOGÍSTICA con statsmodel
          x=df_entrenamiento_under[['V1','V6','V12','V14','V15','V18']]
In [45]:
          y=df_entrenamiento_under['Class']
```

In [48]:

#Aprendiendo

logit= sm.Logit(y,x)
resultado=logit.fit()

Optimization terminated successfully.

Iterations 12

Current function value: 0.070163

In [49]: #Resumiendo
resultado.summary2()

0.896

Logit Pseudo R-squared:

Out[49]:

Model:

Dependent Variable: 112.4734 Class Date: 2021-05-10 22:40 BIC: 139.9155 No. Observations: 716 Log-Likelihood: -50.237 -485.15 Df Model: 5 LL-Null: Df Residuals: 710 LLR p-value: 9.0266e-186 1.0000 Converged: 1.0000 Scale: No. Iterations: 12.0000 Coef. Std.Err. P>|z| [0.025 0.975] z **V1** -2.0041 0.3647 -5.4958 0.0000 -2.7188 -1.2894 1.8428 0.3999 4.6076 0.0000 1.0589 2.6267 **V12** -1.5649 0.4899 -3.1942 0.0014 -2.5251 -0.6047 **V14** -1.2194 0.2861 -4.2618 0.0000 -1.7801 -0.6586 **V15** -2.3595 -5.4533 0.0000 -3.2075 -1.5115 0.4327 **V18** -1.1092 0.4923 -2.2531 0.0243 -2.0741 -0.1443

In []: