###importar librerías In [8]: import matplotlib.pyplot as plt import pandas as pd import numpy as np from sklearn.linear\_model import LogisticRegression from sklearn.metrics import confusion\_matrix, roc\_curve, roc\_auc\_score, accuracy\_score, classification\_report from sklearn.decomposition import PCA, KernelPCA from sklearn.preprocessing import StandardScaler from sklearn.model\_selection import train\_test\_split from sklearn import preprocessing from matplotlib.colors import ListedColormap ###extraer base y visualizar In [4]: df = pd.read\_csv('data1.csv') df.head() customerID tenure PhoneService MultipleLines InternetService OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV StreamingMovies Co Out[4]: 0002-9 0 0 0 0 0 0 1 DSL 1 1 1 ORFBO 0003-1 0 0 0 9 1 DSL 0 0 1 1 **MKNFE** 2 0004-TLHLJ 0 0 0 0 4 1 0 Fiber optic 1 0 3 0011-IGKFF 0 0 Fiber optic 0 1 1 13 1 1 0013-3 1 0 Fiber optic 0 0 0 1 1 0 **EXCHZ** ###limpiar base In [5]: df = df.dropna() df = df.drop\_duplicates() df = df[['tenure', 'PhoneService', 'MultipleLines', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'Streaming' df.head() df.describe() tenure PhoneService MultipleLines OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV StreamingMovies PaperlessBilling Mor Out[5]: count 7043.000000 7043.000000 7043.000000 7043.000000 7043.000000 7043.000000 7043.000000 7043.000000 7043.000000 7043.000000 32.371149 0.903166 0.615505 0.720006 0.778220 0.777226 0.723555 0.817691 0.821241 0.592219 mean 24.559481 0.295752 0.656039 0.763212 std 0.796885 0.778472 0.778826 0.795896 0.761725 0.491457 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 min 25% 9.000000 1.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 **50%** 29.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 **75**% 55.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 72.000000 2.000000 2.000000 max 1.000000 2.000000 2.000000 2.000000 2.000000 2.000000 1.000000 In [10]: ###definición de variables y separacion de train y test df.info() X = df[['tenure', 'PhoneService', 'MultipleLines','OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV y =df['Churn']  $X_{train}, X_{test}, y_{train}, y_{test} = train_{test}, y_{train}, x_{test}, y_{train}, y_{test}, y_{test},$ df.head() <class 'pandas.core.frame.DataFrame'> Int64Index: 7043 entries, 0 to 7042 Data columns (total 12 columns): Non-Null Count Dtype # Column 7043 non-null 0 tenure int64 PhoneService 7043 non-null int64 1 7043 non-null 2 MultipleLines int64 7043 non-null 3 OnlineSecurity int64 int64 4 OnlineBackup 7043 non-null DeviceProtection 7043 non-null 5 int64 TechSupport 7043 non-null 6 int64 StreamingTV 7043 non-null 7 int64 StreamingMovies 7043 non-null 8 int64 PaperlessBilling 7043 non-null int64 9 MonthlyCharges float64 10 7043 non-null 11 Churn 7043 non-null int64 dtypes: float64(1), int64(11)memory usage: 715.3 KB tenure PhoneService MultipleLines OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV StreamingMovies PaperlessBilling MonthlyCharge Out[10]: 0 0 1 0 1 1 0 1 65 0 0 1 9 59 2 4 1 0 0 0 1 0 0 0 1 73 3 13 0 0 98 1 0 0 0 4 3 1 0 0 1 1 1 83 ###transformar datos para la unificación de variables normalización In [12]: sc = StandardScaler() X\_train = sc.fit\_transform(X\_train) X\_test = sc.transform(X\_test) scaler = StandardScaler() scaler.fit(df) scaled\_data = scaler.transform(df) ###reducir el número de características In [13]:  $pca = PCA(n_components=2)$ pca.fit(scaled\_data) X\_pca = pca.transform(scaled\_data) ###ver dimensiones shape print(scaled\_data.shape) print('Reducción de dimensionalidad con shape') print(X\_pca.shape) #pca.fit(X) (7043, 12) Reducción de dimensionalidad con shape (7043, 2)In [14]: ###Gráfica plt.figure(figsize=(8,6)) plt.scatter(X\_pca[:,0], X\_pca[:,1], c=y, cmap='rainbow') plt.xlabel('First principal component') plt.ylabel('Second Principal Component') plt.show() Second Principal Component 2 1 0 First principal component In [16]: ###reducir variable x X\_train = pca.fit\_transform(X\_train)  $X_{\text{test}} = pca.transform(X_{\text{test}})$  $\# X_{pca} = pca.transform(X)$ In [17]: # print(X.shape) # print(X\_pca.shape) X.head() Out[17]: tenure PhoneService MultipleLines OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV StreamingMovies PaperlessBilling MonthlyCharge 0 0 0 0 1 1 59 0 0 0 0 0 0 73 2 1 1 1 13 98 1 0 0 0 0 1 0 1 83 4 3 1 In [18]: #visualizar nuestras reducciones print('Componentes Principales', pca.components\_) print('Varianza explicada', pca.explained\_variance\_) print('Tasa de varianza explicada', pca.explained\_variance\_ratio\_) Componentes Principales [[1. 0.] [0. 1.]] Varianza explicada [5.35162717 1.70076507] Tasa de varianza explicada [0.75883856 0.24116144] #Realización del modelo In [22]: clf = LogisticRegression(random\_state=0) model = clf.fit(X\_train, y\_train) print(model.intercept\_) print(model.coef\_) print('Matriz de probabilidades') print('Prob = 0, Prob = 1') print(model.predict\_proba(X\_train)) print('----') print(model.score(X\_train, y\_train)) [0.00802586] [[-0.18263634 -0.1463361 ]] Matriz de probabilidades Prob = 0, Prob = 1[[0.4996591 0.5003409] [0.69997692 0.30002308] [0.60012895 0.39987105] [0.41933397 0.58066603] [0.67152887 0.32847113] [0.49707887 0.50292113]] 0.585395537525355 In [23]: print(X\_train) print('---- y\_train') print(y\_train) [[-0.08316177 0.14931812] [ 4.11608836 0.7070469 ] [-0.83915568 3.87661437] [-1.05570872 -0.85195292] [ 4.29876393 -0.42352216] [ 0.45332162 -0.59077563]] ----- y\_train 3580 2364 0 6813 0 789 1 561 0 4931 1 3264 1 1653 0 2607 1 2732 0 Name: Churn, Length: 4930, dtype: int64 In [24]: ###Predicción y\_pred = clf.predict(X\_test) print(y\_pred)  $[1 \ 1 \ 0 \ \dots \ 1 \ 0 \ 0]$ In [25]: ###Matriz de confusión cm = confusion\_matrix(y\_test, y\_pred) print(cm) [[470 582] [322 739]] ###Graficar matriz de confusión In [26]: fig, ax = plt.subplots(figsize=(8, 8)) ax.imshow(cm) ax.grid(False) ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted Os', 'Predicted 1s')) ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual Os', 'Actual 1s'))  $ax.set_ylim(1.5, -0.5)$ for i in range(2): for j in range(2): ax.text(j, i, cm[i, j], ha='center', va='center', color='red') plt.show() Actual 0s -Actual 1s Predicted 0s Predicted 1s ###Condicionar el tipo de datos para separar train vs test In [28]: def print\_score(clf, X\_train, X\_test, y\_train, y\_test, train=True): lb = preprocessing.LabelBinarizer() lb.fit(y\_train) if train: training process res = clf.predict(X\_train) print("Train Result: \n") print("Accuracy score: {0:.4f}\n".format(accuracy\_score(y\_train, res))) print("Classification Report: \n {}\n".format(classification\_report(y\_train, res))) print("Confussion Matrix: \n {}\n".format(confusion\_matrix(y\_train, res))) print("ROC AUC: {0:.4f}\n".format(roc\_auc\_score(lb.transform(y\_train), lb.transform(res)))) elif train == False: res\_test = clf.predict(X\_test) print("Train Result: \n") print("Accuracy score: {0:.4f}\n".format(accuracy\_score(y\_test, res\_test))) print("Classification Report: \n {}\n".format(classification\_report(y\_test, res\_test))) print("Confussion Matrix: \n {}\n".format(confusion\_matrix(y\_test, res\_test))) print("ROC AUC: {0:.4f}\n".format(roc\_auc\_score(lb.transform(y\_test), lb.transform(res\_test)))) In [29]: ###Imprimir los resultados print\_score(clf, X\_train, X\_test, y\_train, y\_test, train=True ) Train Result: Accuracy score: 0.5854 Classification Report: precision recall f1-score support 0 0.61 0.45 0.52 2449 1 0.57 0.72 0.63 2481 accuracy 0.59 4930 macro avg 0.59 0.58 0.58 4930 weighted avg 0.59 0.59 0.58 4930 Confussion Matrix: [[1109 1340] [ 704 1777]] ROC AUC: 0.5845