English is not my mother tongue, excuse me for my grammar

Credit Risk

The origin of the data is unknown, the owners do not describe its origin and there is no description, but dataSet is fine to create a model for practice. (https://www.kaggle.com/datasets/essouvenirsama/credit-risk-dataset)

Context

The main goal is create a model that classifies the credit risk of the people who request a loan with the banck according to age of person, annual income, type of homeownership, lenght of employment in year, purpose of the loan, The grade of the loan, the amount of the loan, interest rate of the loan, percentage of the person's annual income that loan represents, whether the person has had a deafult in the past, the lenght of the person's credit history in year.

ML Method

- We will scaling data for better performance
- Before building model we will use PCA for dimensionality
- In this project we will use Logistic Regression

Attributes

- person_age: The age of the person applying for the loan.
- person_income: The annual income of the person.
- person_home_ownership: The type of home ownership of the person (RENT = Rent, OWN = Own, MORTGAGE = Mortgage).
- person_emp_length: The length of employment of the person in years.
- loan_intent: The purpose of the loan (PERSONAL = Personal, EDUCATION = Education, MEDICAL = Medical, VENTURE = Venture, HOMEIMPROVEMENT = Home improvement, DEBTCONSOLIDATION = Debt consolidation).
- loan_grade: The grade of the loan, which is an assessment of the credit risk of the borrower.
- loan_amnt: The amount of the loan requested.
- loan_int_rate: The interest rate of the loan.
- loan_status: The status of the loan (1 = default, 0 = no default).
- loan_percent_income: The percentage of the person’s annual income that the loan represents.
- cb_person_default_on_file: Whether the person has had a default in the past (Y = Yes, N = No).
- cb_person_cred_hist_length: The length of the person’s credit history in years.

In [ ]:
```
# Import libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap # Allows create palette from a list of cc
import seaborn as sns
sns.set(style = "whitegrid")

# Import libraries for scalling data and PCA
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.preprocessing import OneHotEncoder, LabelEncoder

# Import libraries for building model
from imblearn.over_sampling import SMOTE
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import confusion_matrix
from imblearn.under_sampling import RandomUnderSampler
from tensorflow.keras import backend as K
from sklearn.metrics import f1_score


print(tf.__version__)
```

```
2.15.0
```

In [ ]:
```
# Import dataSet from google drive
from google.colab import drive

# link drive
drive.mount('/content/drive')
# link file
ruta = '/content/drive/My Drive/db/credit_risk_dataset.csv'
# Save data
df = pd.read_csv(ruta)
```

```
Mounted at /content/drive
```

1. EXPLORATORY DATA ANALYSIS (EDA)

1.1 Data Inspectation

In [ ]:
```
# Show the basic info about the dataSet
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32581 entries, 0 to 32580
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   person_age                  32581 non-null  int64  
 1   person_income               32581 non-null  int64  
 2   person_home_ownership       32581 non-null  object 
 3   person_emp_length           31686 non-null  float64
 4   loan_intent                 32581 non-null  object 
 5   loan_grade                  32581 non-null  object 
 6   loan_amnt                   32581 non-null  int64  
 7   loan_int_rate               29465 non-null  float64
 8   loan_status                 32581 non-null  int64  
 9   loan_percent_income         32581 non-null  float64
 10  cb_person_default_on_file   32581 non-null  object 
 11  cb_person_cred_hist_length  32581 non-null  int64  
dtypes: float64(3), int64(5), object(4)
memory usage: 3.0+ MB
```

In [ ]:
```
# Show all values in the head of dataSet
df.head()
```

Out[ ]:

	person_age	person_income	person_home_ownership	person_emp_length	loan_intent	loan_grade
0	22	59000	RENT	123.0	PERSONAL	D
1	21	9600	OWN	5.0	EDUCATION	B
2	25	9600	MORTGAGE	1.0	MEDICAL	C
3	23	65500	RENT	4.0	MEDICAL	C
4	24	54400	RENT	8.0	MEDICAL	C

In [ ]:
```
# Check categorical variables (person_home_ownership, loan_intent, loan_grade, cb_pers
```

In [ ]:
```
# person_home_ownership
df['person_home_ownership'].value_counts()
```

Out[ ]:
```
person_home_ownership
RENT        16446
MORTGAGE    13444
OWN          2584
OTHER         107
Name: count, dtype: int64
```

In [ ]:
```
# loan_intent
df['loan_intent'].value_counts()
```

Out[ ]:
```
loan_intent
EDUCATION            6453
MEDICAL              6071
VENTURE              5719
PERSONAL             5521
DEBTCONSOLIDATION    5212
HOMEIMPROVEMENT      3605
Name: count, dtype: int64
```

In [ ]:
```
# loan_grade
df['loan_grade'].value_counts()
```

Out[ ]:
```
loan_grade
A    10777
B    10451
C     6458
D     3626
E      964
F      241
G       64
Name: count, dtype: int64
```

In [ ]:
```
# cb_person_default_on_fil
df['cb_person_default_on_file'].value_counts()
```

Out[ ]:
```
cb_person_default_on_file
N    26836
Y     5745
Name: count, dtype: int64
```

In [ ]:
```
# loan_status
df['loan_status'].value_counts()
```

Out[ ]:
```
loan_status
0    25473
1     7108
Name: count, dtype: int64
```

In [ ]:
```
# Check basic statistics
df.describe()
```

Out[ ]:

	person_age	person_income	person_emp_length	loan_amnt	loan_int_rate	loan_status	lo
count	32581.000000	3.258100e+04	31686.000000	32581.000000	29465.000000	32581.000000	
mean	27.734600	6.607485e+04	4.789686	9589.371106	11.011695	0.218164	
std	6.348078	6.198312e+04	4.142630	6322.086646	3.240459	0.413006	
min	20.000000	4.000000e+03	0.000000	500.000000	5.420000	0.000000	
25%	23.000000	3.850000e+04	2.000000	5000.000000	7.900000	0.000000	
50%	26.000000	5.500000e+04	4.000000	8000.000000	10.990000	0.000000	
75%	30.000000	7.920000e+04	7.000000	12200.000000	13.470000	0.000000	
max	144.000000	6.000000e+06	123.000000	35000.000000	23.220000	1.000000	

In [ ]:
```
# Check if any value is N/A
df.isnull().sum()
```

Out[ ]:
```
person_age                       0
person_income                    0
person_home_ownership            0
person_emp_length              895
loan_intent                      0
loan_grade                       0
loan_amnt                        0
loan_int_rate                 3116
loan_status                      0
loan_percent_income              0
cb_person_default_on_file        0
cb_person_cred_hist_length       0
dtype: int64
```

In [ ]:
```python
# Check if any value is duplicated
df.duplicated().sum()
```

Out[ ]:
```
165
```

- **Note that there are several liers according to the max value, and there are missing values in loan:int_rate.**
- **There are 895 N/A values in person_emp_lenght**
- **There are 3116 N/A values in loan_int_rate**
- **The variable loan_grade provides no information because we don't have context about it.**
- **There are 165 repeat values**

1.2 Data Cleaning and New Features

remove NA values and repeat, drop loan_grade

In [ ]:
```python
# Drop N/A values
df.dropna(inplace = True)
```

In [ ]:
```python
# Drop repeat values
df.drop_duplicates(inplace = True)
```

In [ ]:
```python
# Drop loan_grade
df.drop(['loan_grade'], axis = 1, inplace = True)
```

In [ ]:
```python
df.head()
```

ut[ ]:

	person_age	person_income	person_home_ownership	person_emp_length	loan_intent	loan_amnt	loan_
0	22	59000	RENT	123.0	PERSONAL	35000	
1	21	9600	OWN	5.0	EDUCATION	1000	
2	25	9600	MORTGAGE	1.0	MEDICAL	5500	
3	23	65500	RENT	4.0	MEDICAL	35000	
4	24	54400	RENT	8.0	MEDICAL	35000	

1.3 Get discrete and continous features

We need know wich features are discrete or continous for data visualization

In [ ]:

```
# Divide features by discrete and continous (won't work after PCA)
col_cont = []
col_dis = []

# This secction is taken of the other project by JIESHENDS2020
def divide_feature_types(data):
        '''
        inpute a data frame and output continuous, and discrete feature columns in lis
        '''
        # Initialize
        col_cont=[]
        col_dis=[]
        # loop through and seperate columns
        for c in data.columns:
            if ('person_home_ownership' in c) or ('loan_intent' in c) or ('loan_status
                col_dis.append(c)
            elif (data[c].dtype=='O'):
                col_dis.append(c)
            else:
                col_cont.append(c)
        return col_cont, col_dis

col_cont, col_dis = divide_feature_types(df)
print('Continuous numerical features: ', col_cont)
print('Categorical or discrete features: ', col_dis)
```

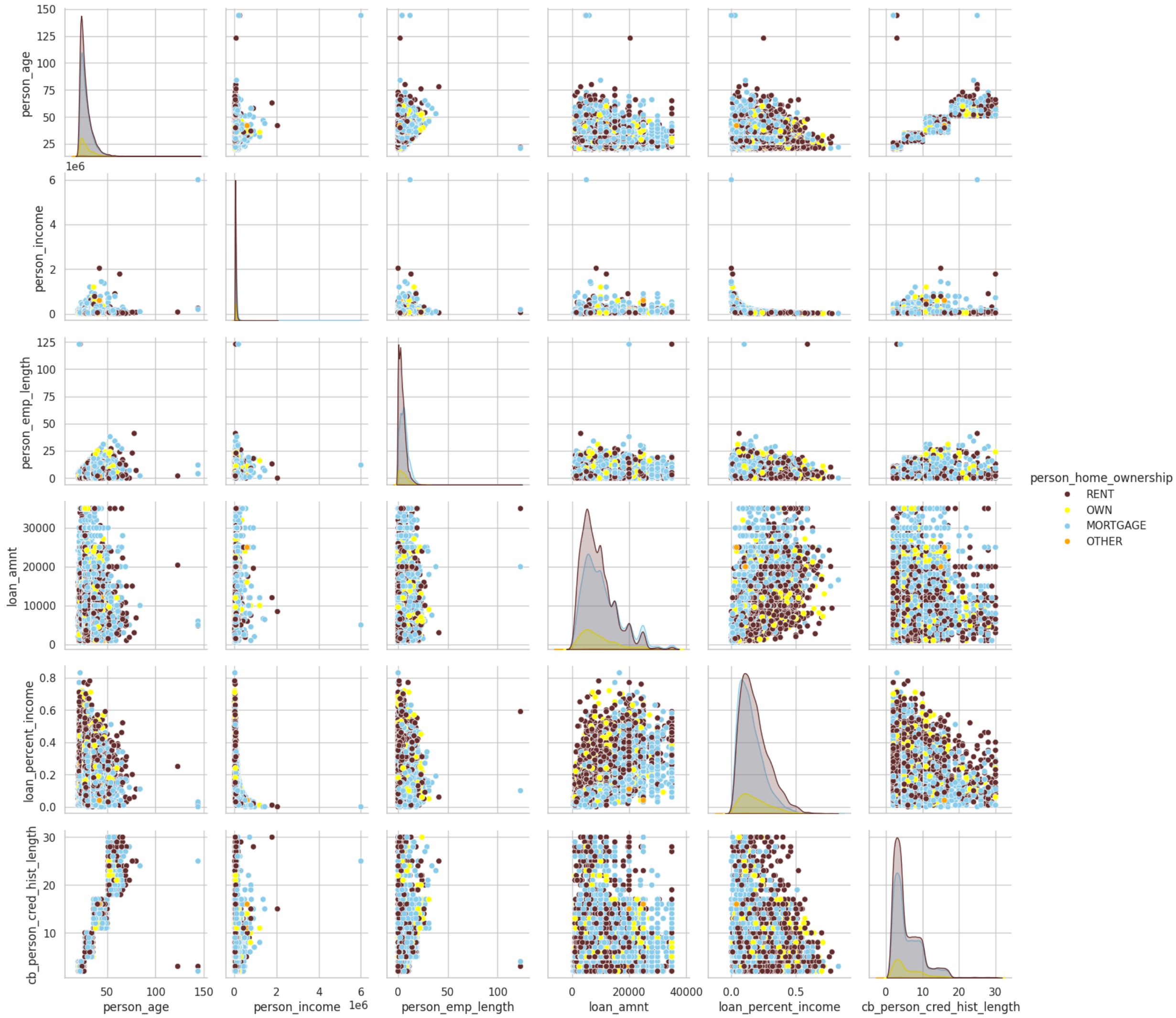
```
Continuous numerical features:  ['person_age', 'person_income', 'person_emp_length',
'loan_amnt', 'loan_int_rate', 'loan_percent_income', 'cb_person_cred_hist_length']
Categorical or discrete features:  ['person_home_ownership', 'loan_intent', 'loan_sta
tus', 'cb_person_default_on_file']
```

1.4 Data visualization analysis

In [ ]:

```
#  Create a pairplot analyzing the continuous variables and relating them to a discret
col_cont_minus_loan_int_rate = [col for col in col_cont if col != 'loan_int_rate']

to_plot = col_cont_minus_loan_int_rate + ['person_home_ownership']
sns.pairplot(df[to_plot], hue = 'person_home_ownership', palette= (["#682F2F","yellow'
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x7ba6dd273af0>

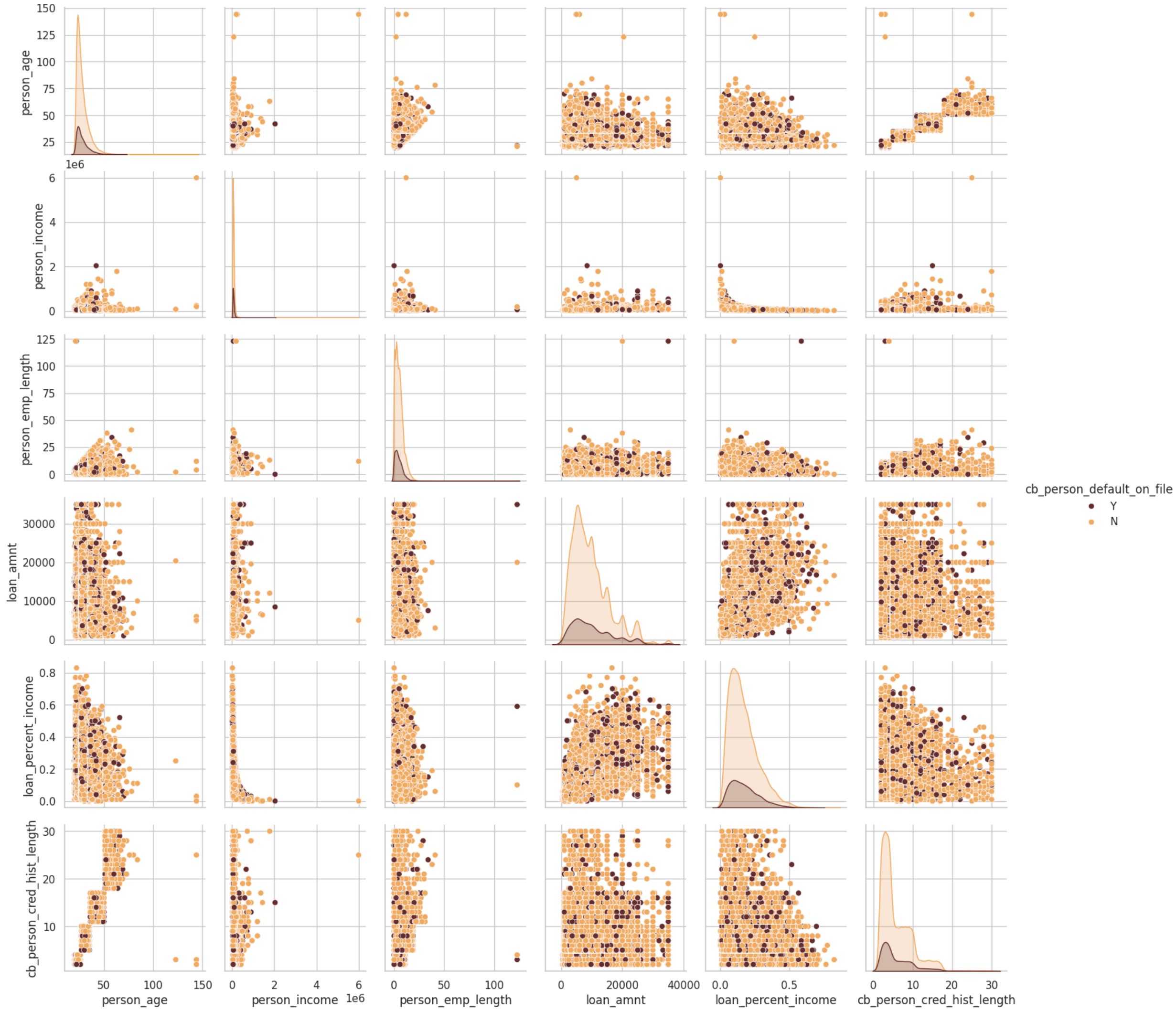


In [ ]:
```
#  Create a pairplot analyzing the continuous variables and relating them to a discret
col_cont_minus_loan_int_rate = [col for col in col_cont if col != 'loan_int_rate']

to_plot = col_cont_minus_loan_int_rate + ['loan_intent']
sns.pairplot(df[to_plot], hue = 'loan_intent', palette= ('colorblind'))
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x7ede265b52d0>

In [ ]:
```
#  Create a pairplot analyzing the continuous variables and relating them to a discret
col_cont_minus_loan_int_rate = [col for col in col_cont if col != 'loan_int_rate']

to_plot = col_cont_minus_loan_int_rate + ['cb_person_default_on_file']
sns.pairplot(df[to_plot], hue = 'cb_person_default_on_file', palette= (["#682F2F","#F3
```

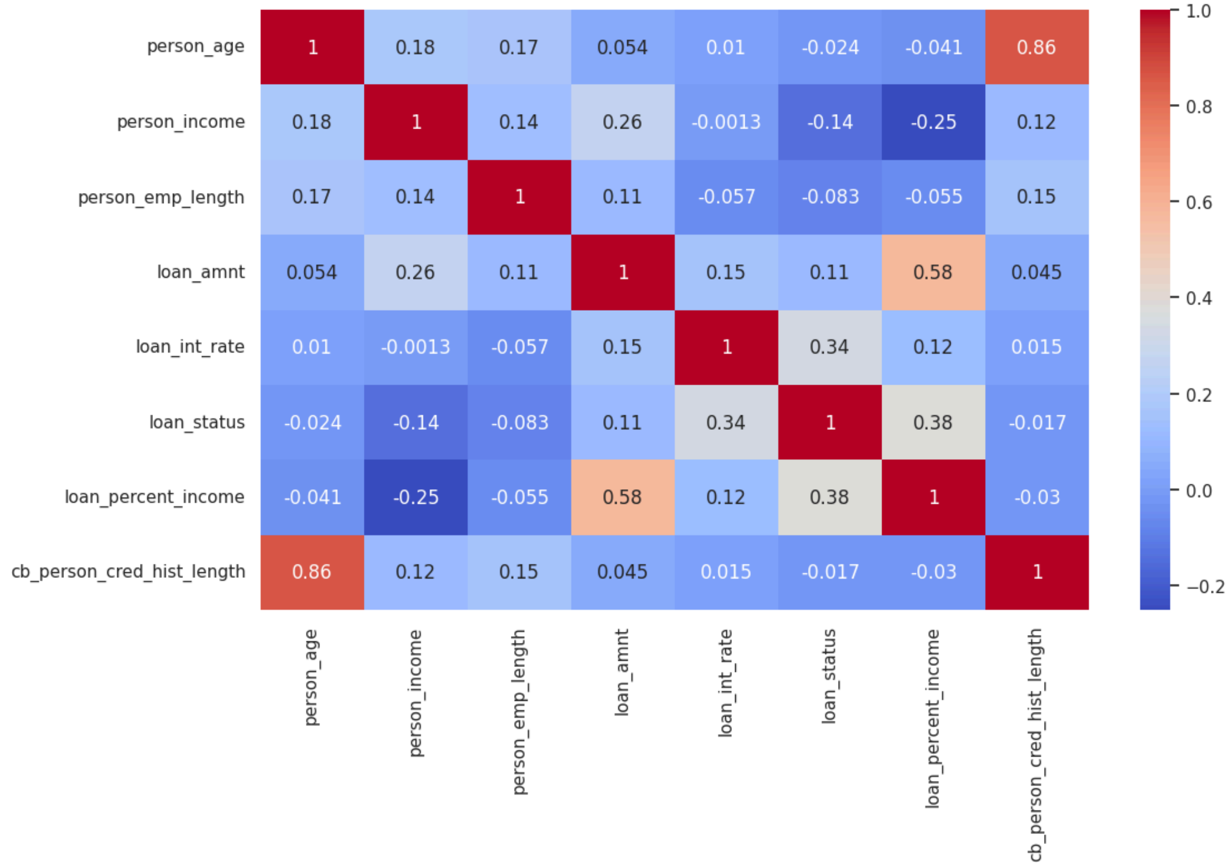
Out[ ]: <seaborn.axisgrid.PairGrid at 0x7ede1c65e650>



In [ ]:
```python
# Create the correlation matriz
plt.figure(figsize = (12, 7))
sns.heatmap(df.corr(), annot = True, cmap = 'coolwarm')
```

```
<ipython-input-21-3de3985d24e0>:3: FutureWarning: The default value of numeric_only i
n DataFrame.corr is deprecated. In a future version, it will default to False. Select
only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot = True, cmap = 'coolwarm')
```

Out[ ]:
```
<Axes: >
```



- **We created a pairplot analyzing the continuous variables relating them to a discrete variables, we can see that there are outliers, in years, in income, and person emplyment years, we will have to do data cleaning again, as for the correlation we can see that there is no presence of multicollinearity.**

1.2 Data Cleaning and New Features (Repeat step)

Drop outliers in person_age, person_income, person_emp_lenght

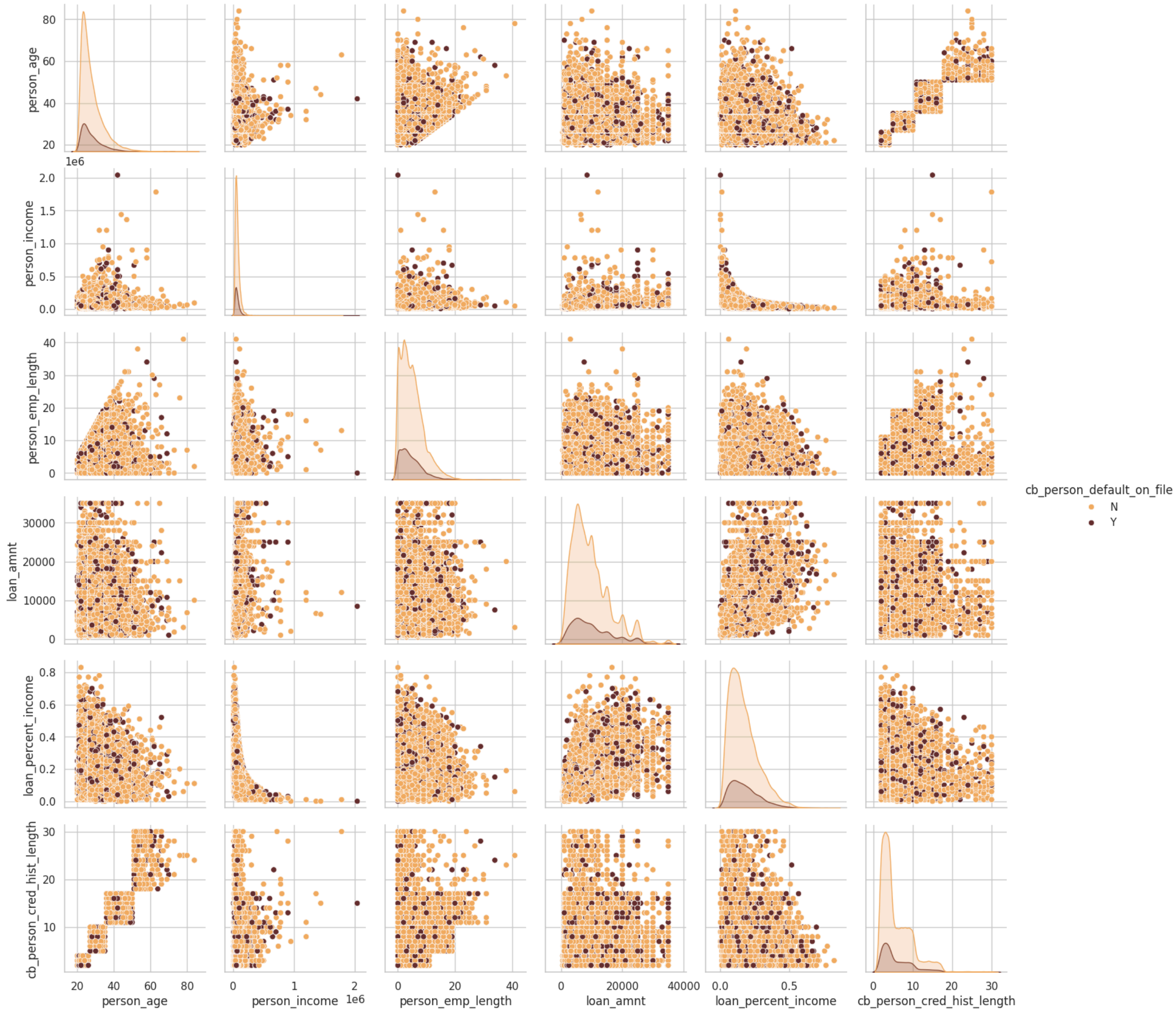
In [ ]:
```
# Drop outliers in person_age
df = df[df['person_age'] < 90]
```

In [ ]:
```
# Drop otliers in person_emp_lenght
df = df[df['person_emp_length'] < 60]
```

1.4 Data visualization analysis (Repeat step)

In [ ]:
```
#  Create a pairplot analyzing the continuous variables and relating them to a discret
col_cont_minus_loan_int_rate = [col for col in col_cont if col != 'loan_int_rate']

to_plot = col_cont_minus_loan_int_rate + ['cb_person_default_on_file']
sns.pairplot(df[to_plot], hue = 'cb_person_default_on_file', palette= (["#F3AB60", "#6
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x7ba6e400f040>



- **Drop the outliers from the data set, now go ahead with data preprocessing**

---

2. DATA PREPROCESSING

In this section we will scalling data for better perfomance to data, also we will get the dummies for categorical variables.

In [ ]:
```
# Obtain categorical variables
le = LabelEncoder()

# Transform person_home_ownership
df['person_home_ownership'] = le.fit_transform(df['person_home_ownership'])

# Transform loan_intent
df['loan_intent'] = le.fit_transform(df['loan_intent'])

# Transform cb_person_defaul_life
df['cb_person_default_on_file'] = le.fit_transform(df['cb_person_default_on_file'])
```

In [ ]:
```
dt = df.copy()
```

In [ ]:
```
# First, we divide the variables into dependent and independent ones
# The binary variables don't scaling
# The target variable is not scaled because it is binary.

dumi = dt['cb_person_default_on_file'].values
y = dt['loan_status'] # Binary dependient
x = dt.drop(['cb_person_default_on_file', 'loan_status'], axis = 1)
```

In [ ]:
```
# Scalling data

# Create data copy
x = x.copy()

# Model
scaler = StandardScaler()

# train model
scaler.fit(x)

# Create new scaler data
x_scaler = pd.DataFrame(scaler.transform(x), columns = x.columns)
```

In [ ]:
```
# Join dummi with x variables
x_scaler['cb_person_default_on_file'] = dumi
```

In [ ]:
```
x_scaler.head()
```

Out[ ]:

	person_age	person_income	person_home_ownership	person_emp_length	loan_intent	loan_amnt
0	-1.088462	-1.103229	0.221743	0.054050	-0.885060	-1.368191
1	-0.440908	-1.103229	-1.172470	-0.936567	0.271360	-0.657021
2	-0.764685	-0.018063	0.918850	-0.193604	0.271360	4.005094
3	-0.602797	-0.233543	0.918850	0.797013	0.271360	4.005094
4	-1.088462	-1.097406	0.221743	-0.688913	1.427781	-1.131134

In [ ]:
```
y.head()
```

Out[ ]:
```
1    0
2    1
3    1
4    1
5    1
Name: loan_status, dtype: int64
```

2. PCA - PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This technique is used to simplify the complexity in high-dimensional data while retaining trends and patterns. It does this by transforming the data into fewer dimensions, which can be easier to interpret and visualize.

In [ ]:
```
# Model
pca = PCA()

# Train model
pca.fit(x_scaler)

# New data PCA_Scales
x_scaler_pca = pca.transform(x_scaler)
```

In [ ]:
```
# Convert DataFrame
x_scaler_pca = pd.DataFrame(x_scaler_pca)
```

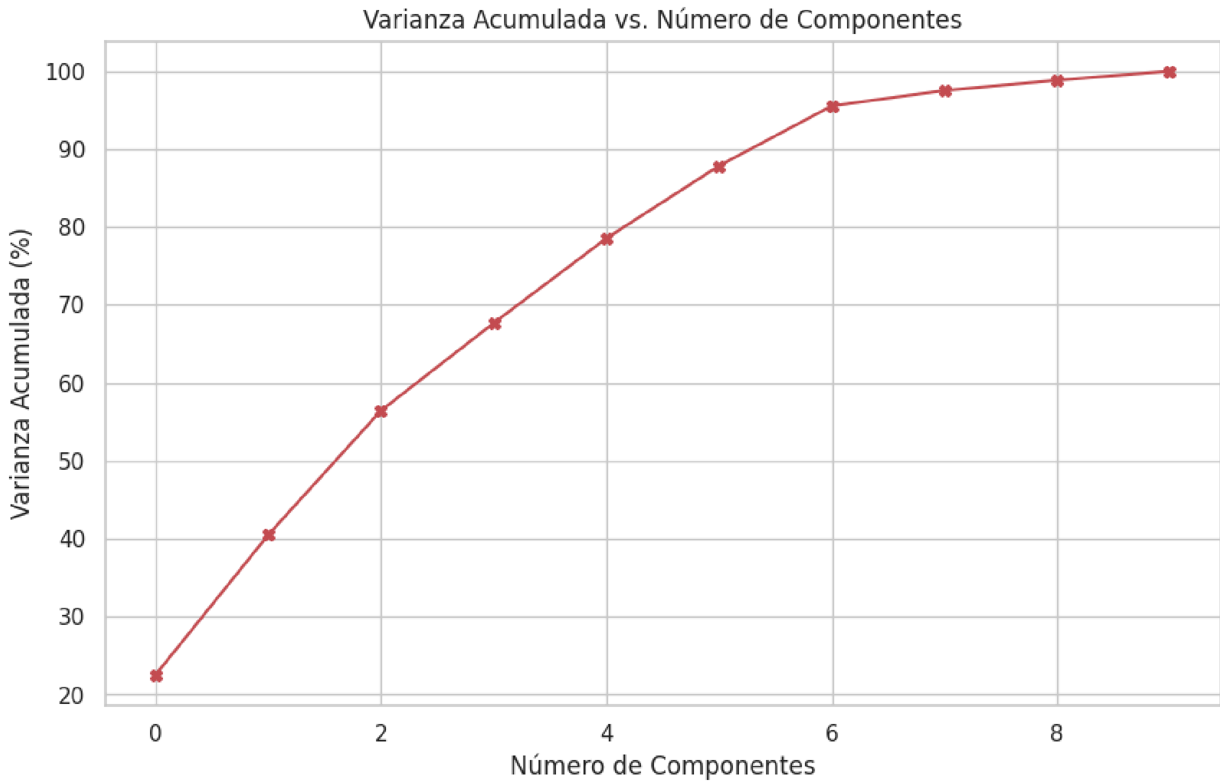
In [ ]:
```
# Now, analyze the variance of data_scaler_pca
var = pca.explained_variance_ratio_

# Show the variance of all features
print(len(var))
print(var)
```

```
10
[0.22532263 0.1796727  0.15939205 0.11234702 0.10877222 0.09314089
 0.07688521 0.01965445 0.01331108 0.01150174]
```

In [ ]:
```
# Chaeck the best option to reduce the dimensionality, for this we plot the variance w
cum_var = np.cumsum(np.round(var, decimals = 4) * 100) # np.cumsum is the cumulative s
# Show results
for i, acumulado in enumerate(cum_var, start=1):
    print(f"{i} componente: {acumulado:.2f}%")

plt.figure(figsize=(10, 6))
plt.plot(cum_var, 'r-x', marker='X')
plt.xlabel('Número de Componentes')
plt.ylabel('Varianza Acumulada (%)')
plt.title('Varianza Acumulada vs. Número de Componentes')
plt.grid(True)
plt.show()
```

```
1 componente: 22.53%
2 componente: 40.50%
3 componente: 56.44%
4 componente: 67.67%
5 componente: 78.55%
6 componente: 87.86%
7 componente: 95.55%
8 componente: 97.52%
9 componente: 98.85%
10 componente: 100.00%
```

```
<ipython-input-32-f53011fee4df>:8: UserWarning: marker is redundantly defined by the 'marker' keyword argument and the fmt string "r-x" (-> marker='x'). The keyword argum
ent will take precedence.
  plt.plot(cum_var, 'r-x', marker='X')
```



In [ ]:

```
x_scaler_pca.head()
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	
0	-1.805493	-1.266667	-0.282448	0.067289	-0.792153	-0.909012	-0.023975	-0.037673	-0.107965	0
1	-1.507392	2.261036	-0.419234	-1.415139	-0.111024	-0.345584	-1.965049	2.322493	0.283426	0
2	-0.949499	5.374103	0.899183	-0.167407	0.348316	0.400812	0.619997	-0.486786	0.085564	0
3	-0.335852	5.446190	0.864788	-0.637231	0.241536	-0.337408	0.960281	-0.404442	-0.099613	-0
4	-1.988344	-0.527045	-0.492026	-1.737870	1.043190	0.385971	-0.203659	0.633875	-0.056493	-0

In [ ]:

```
# Drop components provide no information
x_scaler_pca.drop([7, 8,         9], axis = 1, inplace = True)
```

In [ ]:

```
x_scaler_pca.head()
```

Out[ ]:

	0	1	2	3	4	5	6
0	-1.805493	-1.266667	-0.282448	0.067289	-0.792153	-0.909012	-0.023975
1	-1.507392	2.261036	-0.419234	-1.415139	-0.111024	-0.345584	-1.965049
2	-0.949499	5.374103	0.899183	-0.167407	0.348316	0.400812	0.619997
3	-0.335852	5.446190	0.864788	-0.637231	0.241536	-0.337408	0.960281
4	-1.988344	-0.527045	-0.492026	-1.737870	1.043190	0.385971	-0.203659

7. BUILDING MODEL - LOGISTIC REGRESSION

In [ ]:
```
# Separate data into train and test
x_train, x_test, y_train, y_test = train_test_split(x_scaler_pca, y, test_size = 0.2)
```

In [ ]:
```
df['loan_status'].value_counts()
```

Out[ ]:
```
loan_status
0    22308
1     6187
Name: count, dtype: int64
```

In [ ]:
```
# Balancing data in loan_status - Oversampling
smote = SMOTE(sampling_strategy = 'minority', k_neighbors = 6)
x_train_sm, y_train_sm = smote.fit_resample(x_train, y_train)
```

In [ ]:
```
print(len(x_train_sm))
print(len(y_train_sm))
```

```
35736
35736
```

In [ ]:
```
# Balancing data in loan_status - undersampling
rus = RandomUnderSampler(sampling_strategy='majority')
x_train_us, y_train_us = rus.fit_resample(x_train, y_train)
```

In [ ]:
```
print(len(x_train_us))
print(len(y_train_us))
```

```
9856
9856
```

In [ ]:
```
# Logistic model
model = tf.keras.Sequential([
    tf.keras.layers.Dense(1, activation = 'sigmoid') # The sigmoid function transforms
])


# We compile the model, we create the requirements with which we will evaluate the mod
model.compile(
    loss = 'binary_crossentropy',
    optimizer = 'adam',
    metrics = ['accuracy']
```

```
)

# Train model
model.fit(
    x_train_sm,
    y_train_sm,
    epochs = 100,
    batch_size = 32,
    verbose = 0
)
```

Out[ ]: <keras.src.callbacks.History at 0x7fbf58a5fe80>

In [ ]:
```
# Evaluate model with test set (x_test and y_test)
loss, accuracy = model.evaluate(x_test, y_test)
print(f'Model accuracy : {accuracy*100:.2f}%')
print(f'Average error committed by the model: {loss:.3f}')
```

```
179/179 [==============================] - 0s 1ms/step - loss: 0.4948 - accuracy: 0.7
531
Model accuracy : 75.31%
Average error committed by the model: 0.495
```

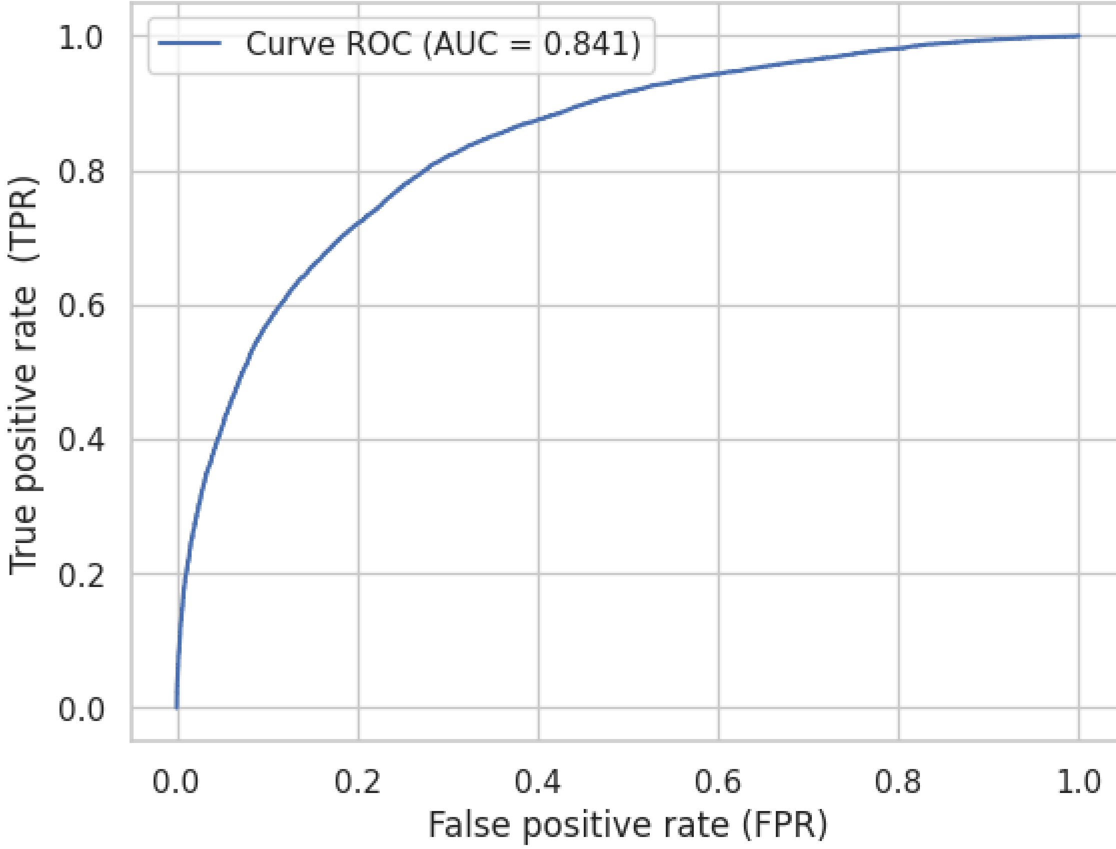
In [ ]:
```
# Prediction with x_train to compare results with y_train
y_pred_train = model.predict(x_train_sm)
```

```
1117/1117 [==============================] - 2s 2ms/step
```

In [ ]:
```
# y_train_sm original
y_train_sm_original = np.array(y_train_sm)
```

In [ ]:
```
# ROC (Receiver Operating Characteristic) curve:
# We create the plot from the predicted data and the actual training data.
# tpr = TRUE POSITIVE RATE (Measures the proportion of positive cases that are correct
# fpr = FALSE POSITIVE RATE (Measures the proportion of negative cases that are incorr
```

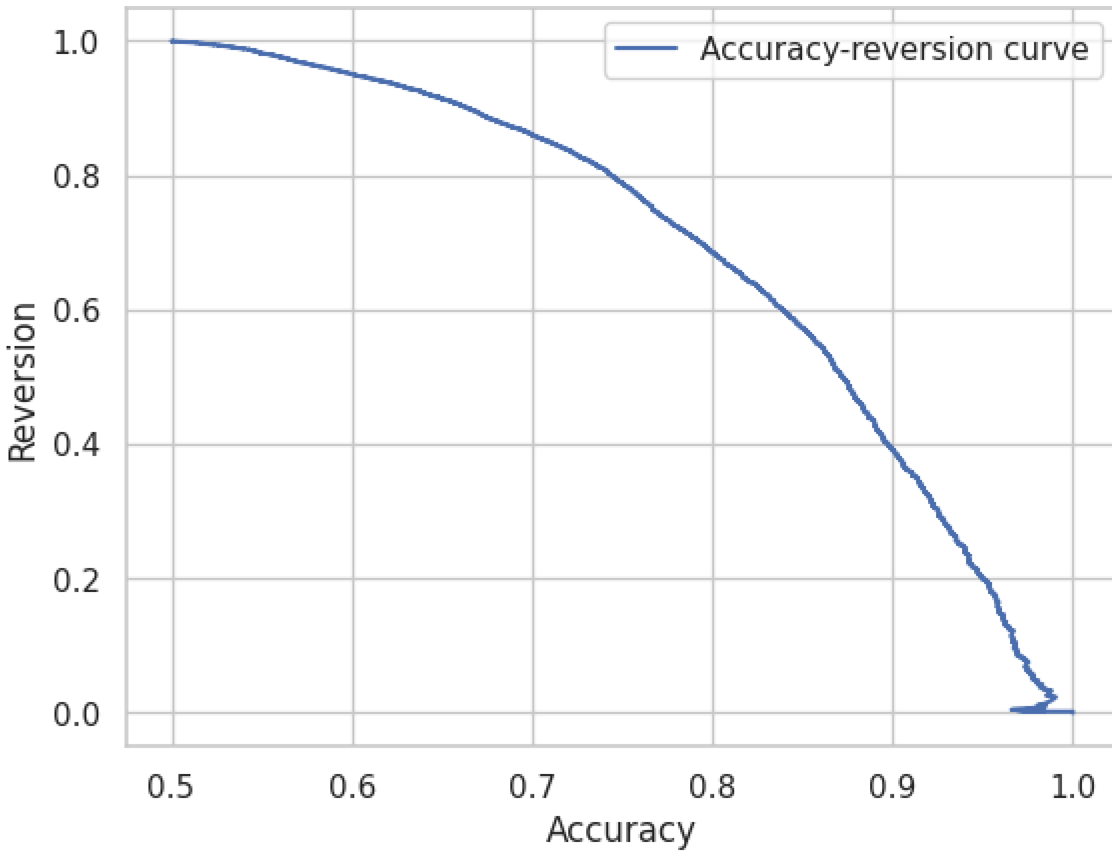
In [ ]:
```
# Curve ROC (Receiver Operating Characteristic)
fpr, tpr, _ = roc_curve(y_train_sm_original, y_pred_train)

# Calculate the area under the ROC curve
auc_score = auc(fpr, tpr)

# Plot
plt.plot(fpr, tpr, label='Curve ROC (AUC = {:.3f})'.format(auc_score))
plt.xlabel('False positive rate (FPR)')
plt.ylabel('True positive rate  (TPR)')
plt.legend()
plt.show()

# Show results
print('An AUC of 0.5 indicates that the model is no better than random at distinguishi
print('An AUC of 1 indicates that the model is perfect at distinguishing between class
```




```
An AUC of 0.5 indicates that the model is no better than random at distinguishing bet
ween classes.
An AUC of 1 indicates that the model is perfect at distinguishing between classes.
```

In [ ]:

```python
# Calculate accuracy and revocation
precision, recall, _ = precision_recall_curve(y_train_sm_original, y_pred_train)


# Plot
plt.plot(precision, recall, label='Accuracy-reversion curve')
plt.xlabel('Accuracy')
plt.ylabel('Reversion')
plt.legend()
plt.show()

# Precision: It focuses on the accuracy of positive predictions. It measures how well
# Recall: It focuses on the completeness of positive predictions. It measures how well
# The main difference between precision and recall lies in their focus:
# Precision: It focuses on the accuracy of positive predictions. It measures how well
# Recall: It focuses on the completeness of positive predictions. It measures how well
# In other words, precision cares about how many of the positive predictions are actua
print('An ideal model would have a precision-recall curve that approaches the upper ri
```



An ideal model would have a precision-recall curve that approaches the upper right corner

In [ ]:
```
# Create the confusion matrix

confusion_matrix = confusion_matrix(y_train_sm, y_pred_train > 0.5)

# Print the confusion matrix
print(confusion_matrix)
```

```
[[13458  4410]
 [ 4062 13806]]
```

In [ ]:
```
print('_______________________________________________________________________________
print('13,377: Cases that the model predicted as positive and are actually positive (T
print('4,440: Cases that the model predicted as positive but are actually negative (Fa
print('3,941: Cases that the model predicted as negative but are actually positive (Fa
print('13,876: Cases that the model predicted as negative and are actually negative (T
print('_______________________________________________________________________________
```

```
____________________________________________________________________________________
____________
13,377: Cases that the model predicted as positive and are actually positive (True positives).
4,440: Cases that the model predicted as positive but are actually negative (False positives).
3,941: Cases that the model predicted as negative but are actually positive (False negatives).
13,876: Cases that the model predicted as negative and are actually negative (True negatives)
____________________________________________________________________________________
____________
```

In [ ]:
```
y_pred_binario = model.predict(x_test) > 0.5
```

```
179/179 [==============================] - 0s 1ms/step
```

In [ ]:
```
f1 = f1_score(y_test, y_pred_binario, average='binary')  # 'binary' para clases desequ
print(f"F1-score: {f1}")
```

```
F1-score: 0.580875781948168
```

The model has an acceptable performance for credit risk prediction.