CIENCIA Y ANALITICA DE DATOS

Actividad Semanal 6 - Visualizacion

Profesor Titular: María de la Paz Rico Fernández

Profesor Tutor: Juan Miguel Meza Méndez

Alumno: Samuel Elias Flores Gonzalez

Matrícula: A01793668

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```
# Modulos, Librerias y Paquetes

import numpy as np
import pandas as pd

import seaborn as sns
import matplotlib as mpl
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.preprocessing import MinMaxScaler, OneHotEncoder, StandardScaler
from sklearn.decomposition import PCA
```

---

1. Cargar los datos

Data Set Information:

This research aimed at the case of customers default payments in Taiwan and compares the predictive accuracy of probability of default among six data mining methods. From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients. Because the real probability of default is unknown, this study presented the novel â€œSorting Smoothing Methodâ€ to estimate the real probability of default. With the real probability of default as the response variable (Y), and the predictive probability of default as the independent variable (X), the simple linear regression result (Y = A + BX) shows that the forecasting model produced by artificial neural network has the highest coefficient of determination; its regression intercept (A) is close to zero, and regression coefficient (B) to one. Therefore, among the six data mining techniques, artificial neural network is the only one that can accurately estimate the real probability of default.

Attribute Information:

This research employed a binary variable, default payment (Yes = 1, No = 0), as the response variable. This study reviewed the literature and used the following 23 variables as explanatory variables: X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit. X2: Gender (1 = male; 2 = female). X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others). X4: Marital status (1 = married; 2 = single; 3 = others). X5: Age (year). X6 - X11: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows: X6 = the repayment status in September, 2005; X7 = the repayment status in August, 2005; . . .;X11 = the repayment status in April, 2005. The measurement scale for the repayment status is: -1 = pay duly; 1 = payment delay for one month; 2 = payment delay for two months; . . .; 8 = payment delay for eight months; 9 = payment delay for nine months and above. X12-X17: Amount of bill statement (NT dollar). X12 = amount of bill statement in September, 2005; X13 = amount of bill statement in August, 2005; . . .; X17 = amount of bill statement in April, 2005. X18-X23: Amount of previous payment (NT dollar). X18 = amount paid in September, 2005; X19 = amount paid in August, 2005; . . .;X23 = amount paid in April, 2005.

Base de datos de aprobación de crédito.

eh, I. C., & Lien, C. H. (2009). The comparisons of data mining techniques for the predictive accuracy of probability of default of credit card clients. Expert Systems with Applications, 36(2), 2473-2480.

```
url = "https://raw.githubusercontent.com/PosgradoMNA/Actividades_Aprendizaje-/main/default%20
```

```
df = pd.read_csv(url)
```

---

2. Informacion del dataframe

```
df.shape #Se verifican dimensiones del dataframe
```

```
(30000, 25)
```

```
df.columns #Se verifican los nombres actuales de las columnas del dataframe
```

```
Index(['ID', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8', 'X9', 'X10',
       'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18', 'X19', 'X20',
       'X21', 'X22', 'X23', 'Y'],
      dtype='object')
```

```
df.head(5) #Se despliegan los primeros 5 datos
```

	ID	Amount_Credit	Gender	Education	Marital_Status	Age	Payment_Sep_2005	Payment
0	1	20000	2.0	2.0	1.0	24.0	2.0	
1	2	120000	2.0	2.0	2.0	26.0	-1.0	
2	3	90000	2.0	2.0	2.0	34.0	0.0	
3	4	50000	2.0	2.0	1.0	37.0	0.0	
4	5	50000	1.0	2.0	1.0	57.0	-1.0	

5 rows × 25 columns

```
#Se reemplazan los nombres de las columnas

df = df.rename(columns = {'X1' : 'Amount_Credit',
                          'X2' : 'Gender',
                          'X3' : 'Education',
                          'X4' : 'Marital_Status',
                          'X5' : 'Age',
                          'X6' : 'Payment_Sep_2005',
                          'X7' : 'Payment_Aug_2005',
                          'X8' : 'Payment_Jul_2005',
                          'X9' : 'Payment_Jun_2005',
                          'X10' : 'Payment_May_2005',
                          'X11' : 'Payment_Apr_2005',
                          'X12' : 'Bill_State_Sep_2005',
                          'X13' : 'Bill_State_Aug_2005',
                          'X14' : 'Bill_State_Jul_2005',
                          'X15' : 'Bill_State_Jun_2005',
                          'X16' : 'Bill_State_May_2005',
                          'X17' : 'Bill_State_Apr_2005',
                          'X18' : 'Previous_Pay_Sep_2005',
                          'X19' : 'Previous_Pay_Aug_2005',
                          'X20' : 'Previous_Pay_Jul_2005',
                          'X21' : 'Previous_Pay_Jun_2005',
                          'X22' : 'Previous_Pay_May_2005',
                          'X23' : 'Previous_Pay_Apr_2005' },
```

```
inplace = False
```

```
df.head(5) #Se vuelven a desplegar los primeros 5 valores del dataframe
```

	ID	Amount_Credit	Gender	Education	Marital_Status	Age	Payment_Sep_2005	Payment
0	1	20000	2.0	2.0	1.0	24.0	2.0	
1	2	120000	2.0	2.0	2.0	26.0	-1.0	
2	3	90000	2.0	2.0	2.0	34.0	0.0	
3	4	50000	2.0	2.0	1.0	37.0	0.0	
4	5	50000	1.0	2.0	1.0	57.0	-1.0	

5 rows × 25 columns

```
df.dtypes
```

```
ID                        int64
Amount_Credit             int64
Gender                  float64
Education               float64
Marital_Status          float64
Age                     float64
Payment_Sep_2005        float64
Payment_Aug_2005        float64
Payment_Jul_2005        float64
Payment_Jun_2005        float64
Payment_May_2005        float64
Payment_Apr_2005        float64
Bill_State_Sep_2005     float64
Bill_State_Aug_2005     float64
Bill_State_Jul_2005     float64
Bill_State_Jun_2005     float64
Bill_State_May_2005     float64
Bill_State_Apr_2005     float64
Previous_Pay_Sep_2005   float64
Previous_Pay_Aug_2005   float64
Previous_Pay_Jul_2005   float64
Previous_Pay_Jun_2005   float64
Previous_Pay_May_2005   float64
Previous_Pay_Apr_2005   float64
Y                       float64
dtype: object
```

```
df.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   Amount_Credit          30000 non-null  int64  
 2   Gender                 29999 non-null  float64
 3   Education              29998 non-null  float64
 4   Marital_Status         29998 non-null  float64
 5   Age                    29995 non-null  float64
 6   Payment_Sep_2005       29997 non-null  float64
 7   Payment_Aug_2005       29995 non-null  float64
 8   Payment_Jul_2005       29993 non-null  float64
 9   Payment_Jun_2005       29991 non-null  float64
 10  Payment_May_2005       29984 non-null  float64
 11  Payment_Apr_2005       29986 non-null  float64
 12  Bill_State_Sep_2005    29989 non-null  float64
 13  Bill_State_Aug_2005    29989 non-null  float64
 14  Bill_State_Jul_2005    29987 non-null  float64
 15  Bill_State_Jun_2005    29985 non-null  float64
 16  Bill_State_May_2005    29983 non-null  float64
 17  Bill_State_Apr_2005    29990 non-null  float64
 18  Previous_Pay_Sep_2005  29992 non-null  float64
 19  Previous_Pay_Aug_2005  29991 non-null  float64
 20  Previous_Pay_Jul_2005  29992 non-null  float64
 21  Previous_Pay_Jun_2005  29989 non-null  float64
 22  Previous_Pay_May_2005  29989 non-null  float64
 23  Previous_Pay_Apr_2005  29995 non-null  float64
 24  Y                      29997 non-null  float64
dtypes: float64(23), int64(2)
memory usage: 5.7 MB
```

```
df.isna()
```

	ID	Amount_Credit	Gender	Education	Marital_Status	Age	Payment_Sep_2005
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False

```
df.isna().values.any() # Se verifica si hay algun dato vacio
```

```
True
```

4	False	False	False	False	False	False	False

3. Limpieza de los datos

29996	False	False	False	False	False	False	False

```
df.dropna(inplace = True)  #Eliminamos los datos NaN o nulos
```

```
df.isna().values.any() #Comprobamos si existen datos nulos
```

```
False
```

4. Calculo de la estadistica descriptiva

```
df.describe()
```

	ID	Amount_Credit	Gender	Education	Marital_Status	
count	29958.000000	29958.000000	29958.000000	29958.000000	29958.000000	29958.00
mean	15005.550504	167555.900928	1.604012	1.853094	1.551739	35.48
std	8654.547473	129737.299088	0.489070	0.790471	0.521952	9.21
min	1.000000	10000.000000	1.000000	0.000000	0.000000	21.00
25%	7516.250000	50000.000000	1.000000	1.000000	1.000000	28.00
50%	15005.500000	140000.000000	2.000000	2.000000	2.000000	34.00
75%	22497.750000	240000.000000	2.000000	2.000000	2.000000	41.00
max	30000.000000	1000000.000000	2.000000	6.000000	3.000000	79.00

8 rows × 25 columns

Decidimos eliminar los registros vacios debido a que la cantidad era muy pequeña en comparacion con la cantidad total de registros, es decir se eliminaron 42 registros de 30000, menos del 1%.

Segun la estadistica descriptiva, las columnas o variables que presentan mayor desviacion estandar son: Amount_Credit, los Bill_state y los Previous_Pay; mientras que todas las demas columnas presentas una desviacion estandar alrededor de 0 y 1.

Podemos observar que las columnas presentan distintas magnitudes, es decir mientras que Amount_Credit esta en el orden de los miles, otras variables o columnas estan entre los valores 0 y 1. Esto quiere decir que se debe aplicar una normalizacion a los datos para poder tener una menor diferencia en los rangos de los mismos.

5. Conteo de variables categoricas

Se separan las variables de entrada y la salida.

```
X = df.drop("Y", axis=1) #Eliminamos la columna y y almacenamos dataframe en X
Y = df["Y"]  #Almacenamos columna Y
```

Ahora nos interesa identificar a las variables categoricas para proceder a eliminarlas, puesto que solo nos interesan las numericas

ID, Gender, Education, Marital status, Age, Payment September - April 2005.

```
X = X.drop(['ID', 'Gender', 'Education', 'Marital_Status', 'Age', 'Payment_Sep_2005', 'Paymen
X.head() #Mostramos dataframe con datos numericos
```

	Amount_Credit	Bill_State_Sep_2005	Bill_State_Aug_2005	Bill_State_Jul_2005	Bill_S
0	20000	3913.0	3102.0	689.0	
1	120000	2682.0	1725.0	2682.0	
2	90000	29239.0	14027.0	13559.0	
3	50000	46990.0	48233.0	49291.0	
4	50000	8617.0	5670.0	35835.0	

6. Escalamiento de los datos

Prodemos a escalar los datos para evitar sesgos creados por la diferencias de magnitudes de cada una de las columnas.

```
scaler = MinMaxScaler()                        #Definimos escalamiento
scaled = scaler.fit_transform(X)
scaled_X = pd.DataFrame(scaled, columns=X.columns)  #Realizamos escalamiento
scaled_X.head()
```

	Amount_Credit	Bill_State_Sep_2005	Bill_State_Aug_2005	Bill_State_Jul_2005	Bill_S
0	0.010101	0.149982	0.069164	0.086723	
1	0.111111	0.148892	0.067858	0.087817	
2	0.080808	0.172392	0.079532	0.093789	
3	0.040404	0.188100	0.111995	0.113407	
4	0.040404	0.154144	0.071601	0.106020	

Como se puede obervar, ahora mismo, los datos todas las columnas se encuentran en un rango de 0 a 1.

---

7. Reduccion de dimensiones con PCA

```
pcs = PCA() #Aplicamos PCA
pcs_t = pcs.fit_transform(scaled_X)
pcs_t
```

```
array([[-1.70220739e-01,  4.55874383e-02, -1.20064468e-04, ...,
         3.58960605e-04,  3.36984589e-04,  6.77740494e-04],
       [-9.90982643e-02, -2.60772497e-02, -4.67276907e-03, ...,
         7.06196680e-04, -2.85343235e-04, -3.61080529e-05],
       [-9.70277616e-02,  1.68328789e-02, -1.47786552e-03, ...,
        -5.17236765e-03, -1.22349588e-03, -4.13295690e-04],
       ...,
       [-1.45295136e-01,  5.31650933e-02,  1.57707551e-02, ...,
         4.14252460e-03,  8.99087513e-04, -1.48836952e-03],
       [-5.78218997e-02,  5.70665513e-02,  1.07110150e-01, ...,
```

```
        -1.28164910e-02, -7.85206363e-03, -9.97520841e-03],
       [-9.19042877e-02,  7.78591548e-02, -8.01930001e-03, ...,
        -4.45835633e-05,  7.39169942e-03, -2.01033628e-03]])
```

7.1. Explicacion de la varianza de los datos

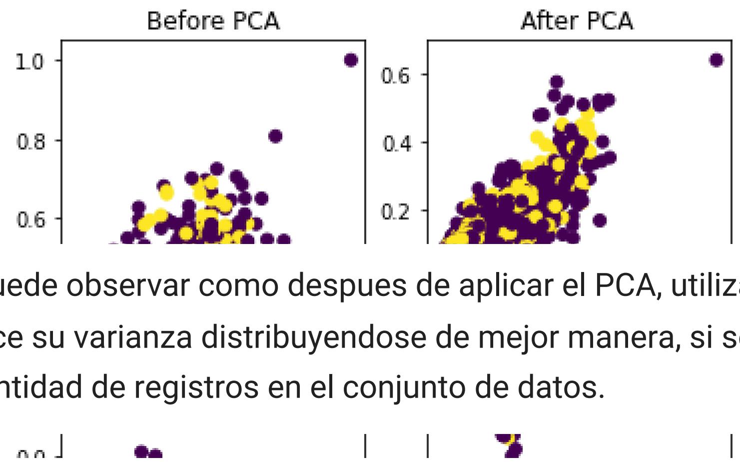
```
pcsSummary_df = pd.DataFrame({'% Varianza Explicada': np.round(pcs.explained_variance_,6) * 1
                              "Desviación Estándar": np.round(np.sqrt(pcs.explained_variance
                              "%Proporción de Varianza": np.round(pcs.explained_variance_rat
                              '% Varianza Acumulada': np.round(np.cumsum(pcs.explained_varia
                             })
pcs_labels = [f'PC{i + 1}' for i in range(len(scaled_X.columns))]
pcsSummary_df.index = pcs_labels
pcsSummary_df = pcsSummary_df.round(2).transpose()
pcsSummary_df
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	P
% Varianza Explicada	2.31	1.22	0.14	0.11	0.10	0.06	0.04	0.04	0.02	0.01	0.01	(
Desviación Estándar	0.15	0.11	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.01	(
%Proporción de Varianza	56.50	29.90	3.30	2.80	2.50	1.50	1.10	0.90	0.60	0.40	0.30	(

Como vemos en la tabla, las primeras dos componentes prinpipales nos explican el 86.5%, por lo cual podemos decir que este es el nímero minimos de componentes principales. A partir de la tercera componente la varianza explicada es muy pequeña como para ser considerada.

Double-click (or enter) to edit

```
fig, axes = plt.subplots(1,2)
axes[0].scatter(scaled_X["Amount_Credit"], scaled_X["Bill_State_Sep_2005"], c=Y)
axes[0].set_title('Before PCA')
axes[1].scatter(pcs_t[:,0], pcs_t[:,1], c=Y)
axes[1].set_title('After PCA')
plt.show()
```



Se puede observar como despues de aplicar el PCA, utilizando las dos primeras componentes, se reduce su varianza distribuyendose de mejor manera, si se visualizan demasiado juntas es debido a la cantidad de registros en el conjunto de datos.

7.2. Importancia de las variables de cada componente

```
pcsComponents_df = pd.DataFrame(pcs.components_.transpose(),
                                columns=['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC
                                index=X.columns
                                )
pcsComponents_df.round(3)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	
Amount_Credit	0.681	-0.727	-0.077	-0.022	-0.025	-0.015	-0.015	-0.011	-0.004	-
Bill_State_Sep_2005	0.334	0.317	-0.194	0.424	-0.229	0.231	-0.204	0.366	0.088	
Bill_State_Aug_2005	0.350	0.343	-0.177	0.329	-0.161	0.106	0.276	-0.225	-0.271	-
Bill_State_Jul_2005	0.196	0.188	-0.021	0.041	-0.012	-0.106	0.105	-0.247	0.534	
Bill_State_Jun_2005	0.317	0.298	0.028	-0.227	0.155	-0.395	0.138	0.194	0.187	-
Bill_State_May_2005	0.313	0.289	0.095	-0.429	0.260	0.074	-0.197	-0.099	-0.128	
Bill_State_Apr_2005	0.232	0.212	0.240	-0.332	-0.026	-0.020	-0.232	-0.136	-0.259	
Previous_Pay_Sep_2005	0.034	0.004	0.097	0.028	0.092	0.054	0.712	-0.322	-0.245	
Previous_Pay_Aug_2005	0.020	-0.002	0.094	-0.031	0.064	-0.030	0.223	-0.031	0.626	
Previous_Pay_Jul_2005	0.035	-0.001	0.140	-0.095	0.141	-0.017	0.406	0.762	-0.148	
Previous_Pay_Jun_2005	0.043	-0.004	0.215	-0.124	0.196	0.855	0.048	0.019	0.193	-
Previous_Pay_May_2005	0.062	-0.013	0.816	0.150	-0.501	-0.084	-0.018	0.004	0.018	-
Previous_Pay_Apr_2005	0.057	-0.014	0.329	0.562	0.712	-0.141	-0.186	-0.057	-0.063	

```
pcsComponents_df.PC1.abs().idxmax()
```

```
'Amount_Credit'
```

```
pcsComponents_df.PC2.abs().idxmax()
```

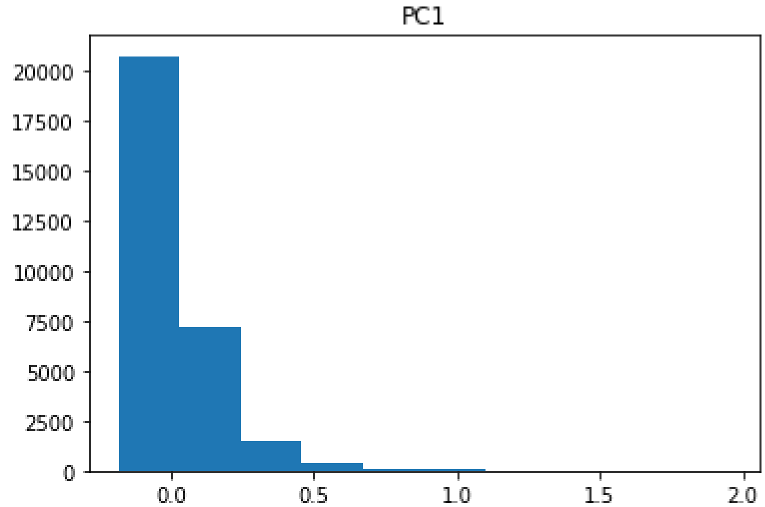
```
'Amount_Credit'
```

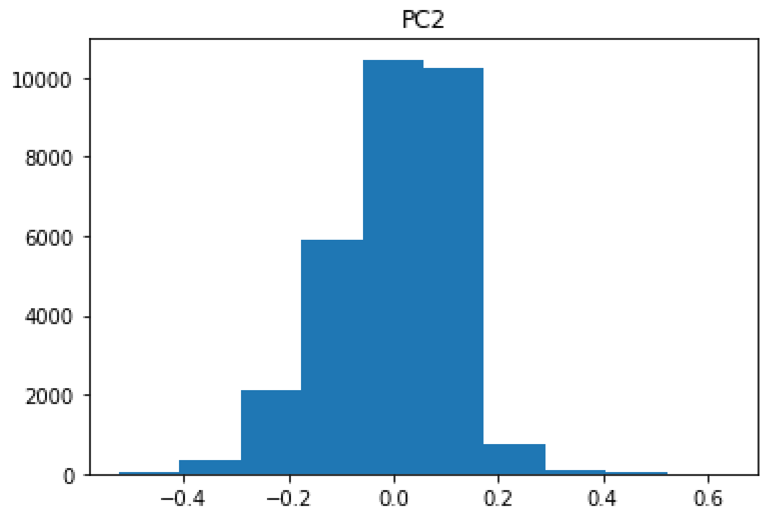
Observamos que tanto la componente 1 y 2 tienen un mayor peso sobre la variable Amount_Credit

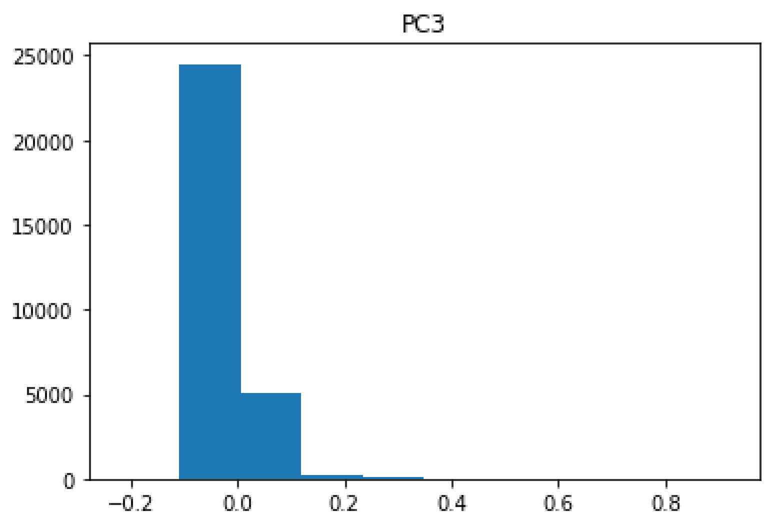
---

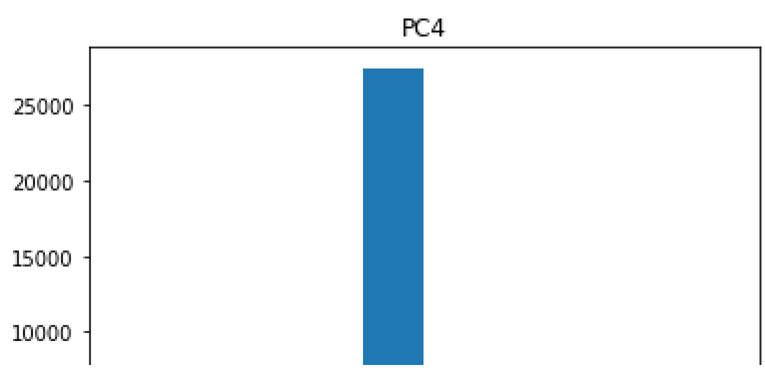
8. Histograma de los atributos

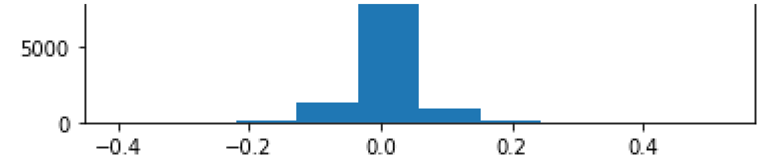
```
fig, ax = plt.subplots()
for i in range(0,13):
  plt.hist(pcs_t[:,i])
  plt.title("PC%d"%(i+1))
  plt.show()
```

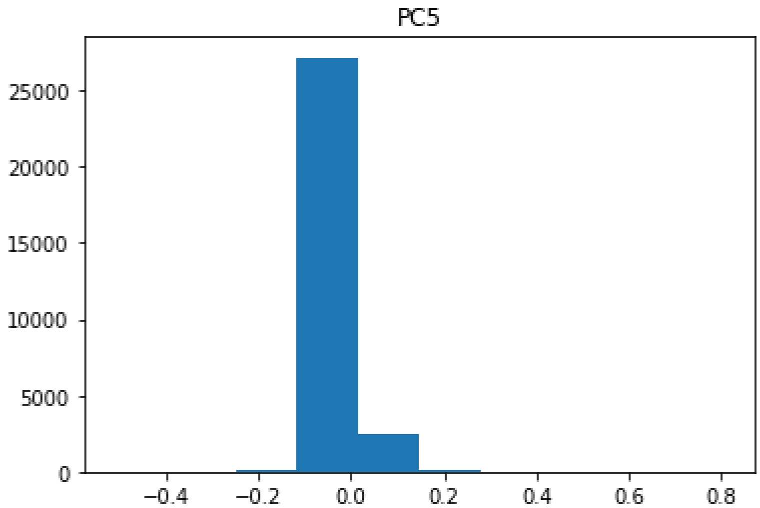

PC1
0
2500
5000
7500
10000
12500
15000
17500
20000
0.0
0.5
1.0
1.5
2.0

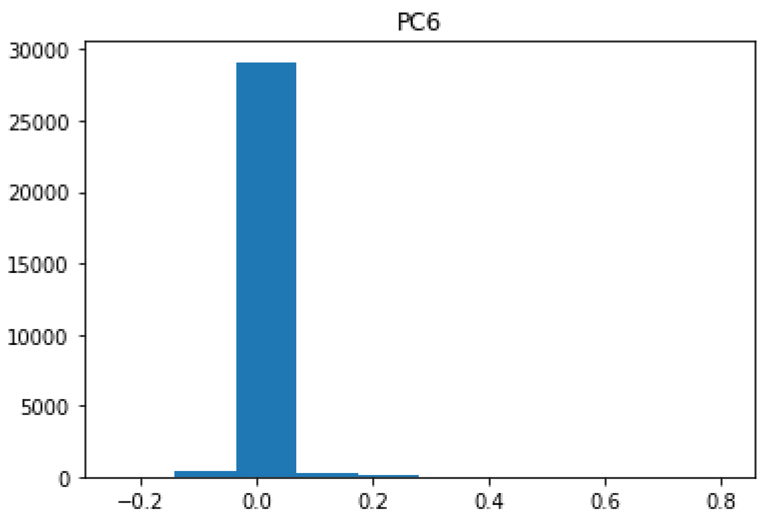

PC2
0
2000
4000
6000
8000
10000
−0.4
−0.2
0.0
0.2
0.4
0.6

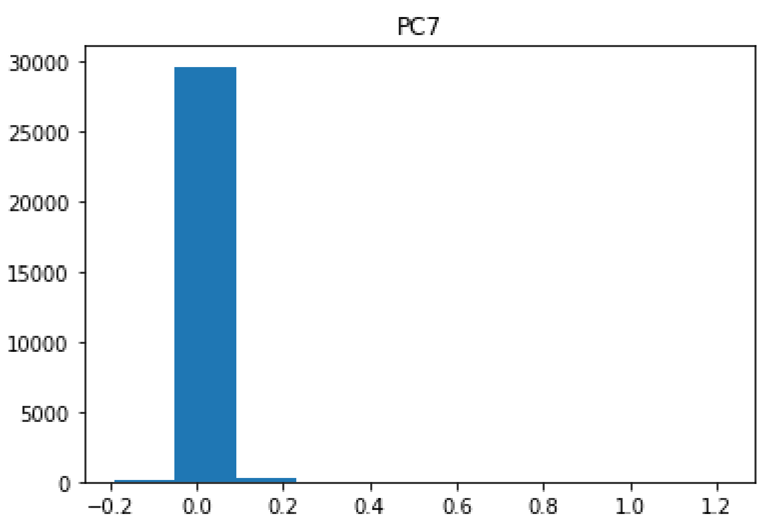

PC3
0
5000
10000
15000
20000
25000
−0.2
0.0
0.2
0.4
0.6
0.8

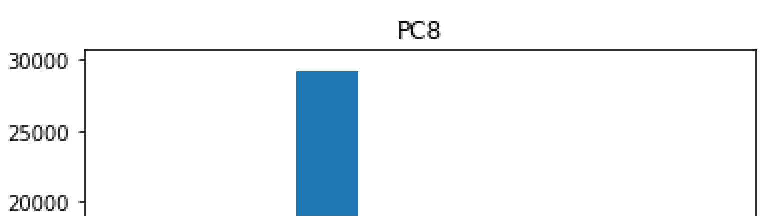

PC4
10000
15000
20000
25000

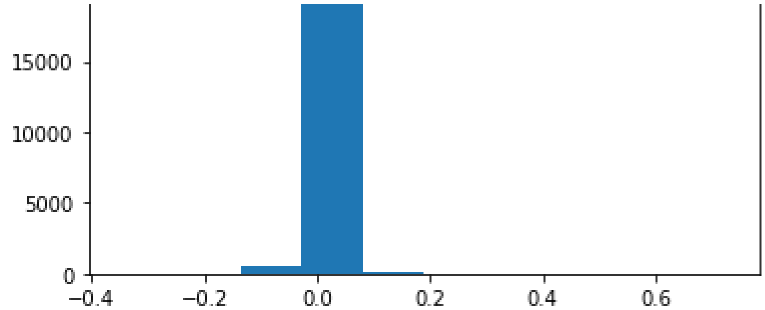

5000
0
−0.4
−0.2
0.0
0.2
0.4


PC5
25000
20000
15000
10000
5000
0
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8

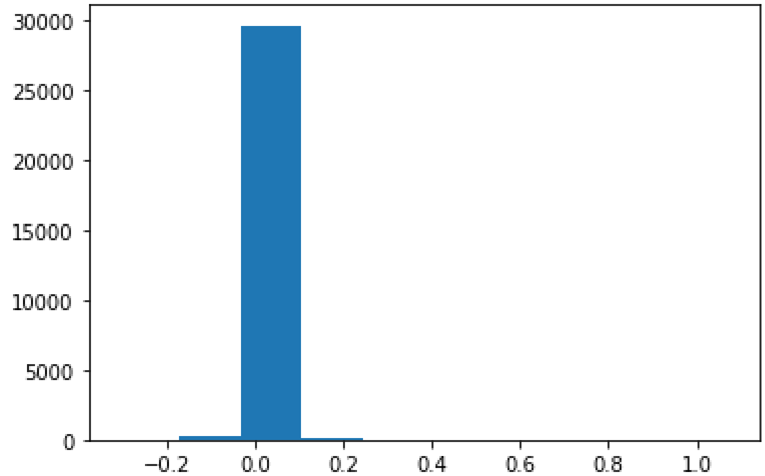

PC6
30000
25000
20000
15000
10000
5000
0
−0.2
0.0
0.2
0.4
0.6
0.8


PC7
30000
25000
20000
15000
10000
5000
0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2

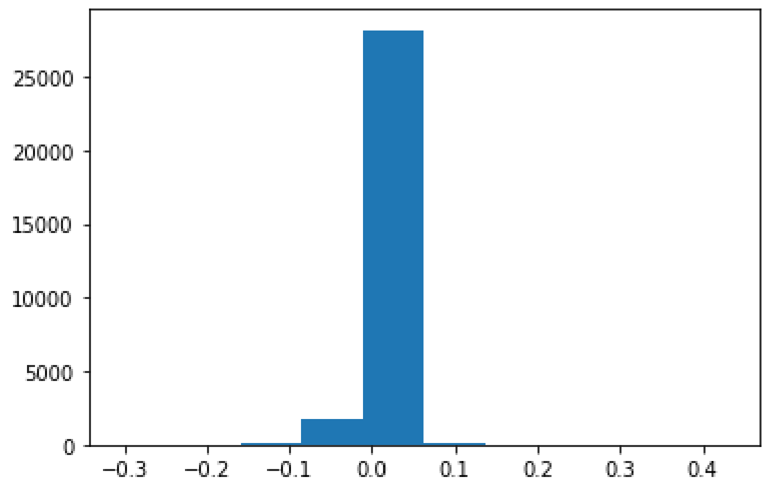

PC8
30000
25000
20000



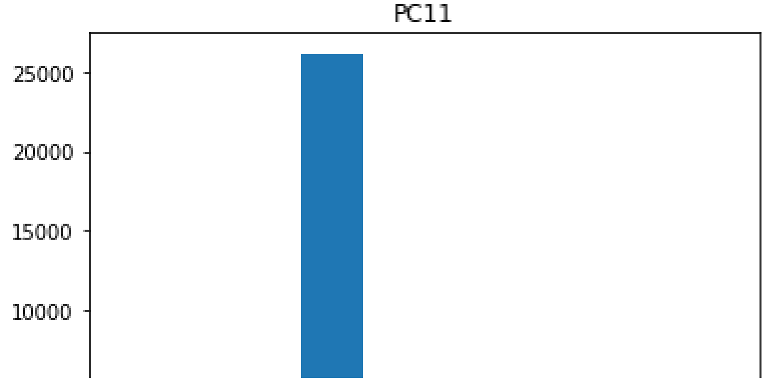
PC9



PC10



PC11

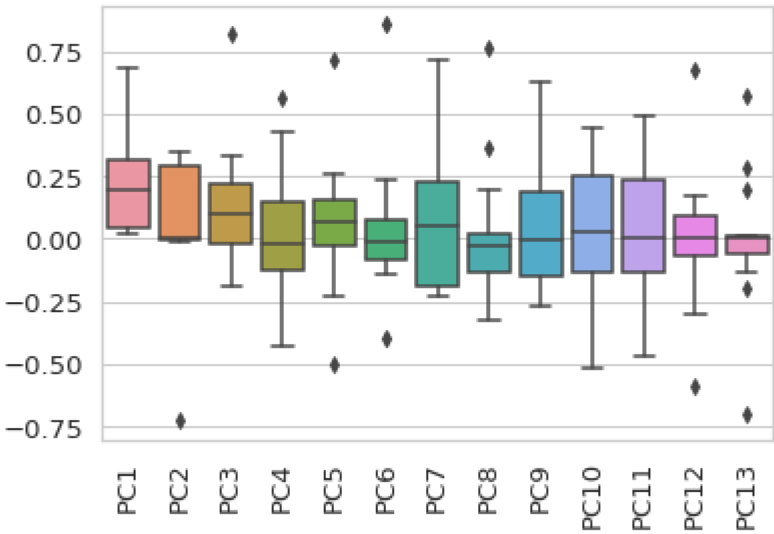


9. Visualizacion de los datos usando 3 graficos

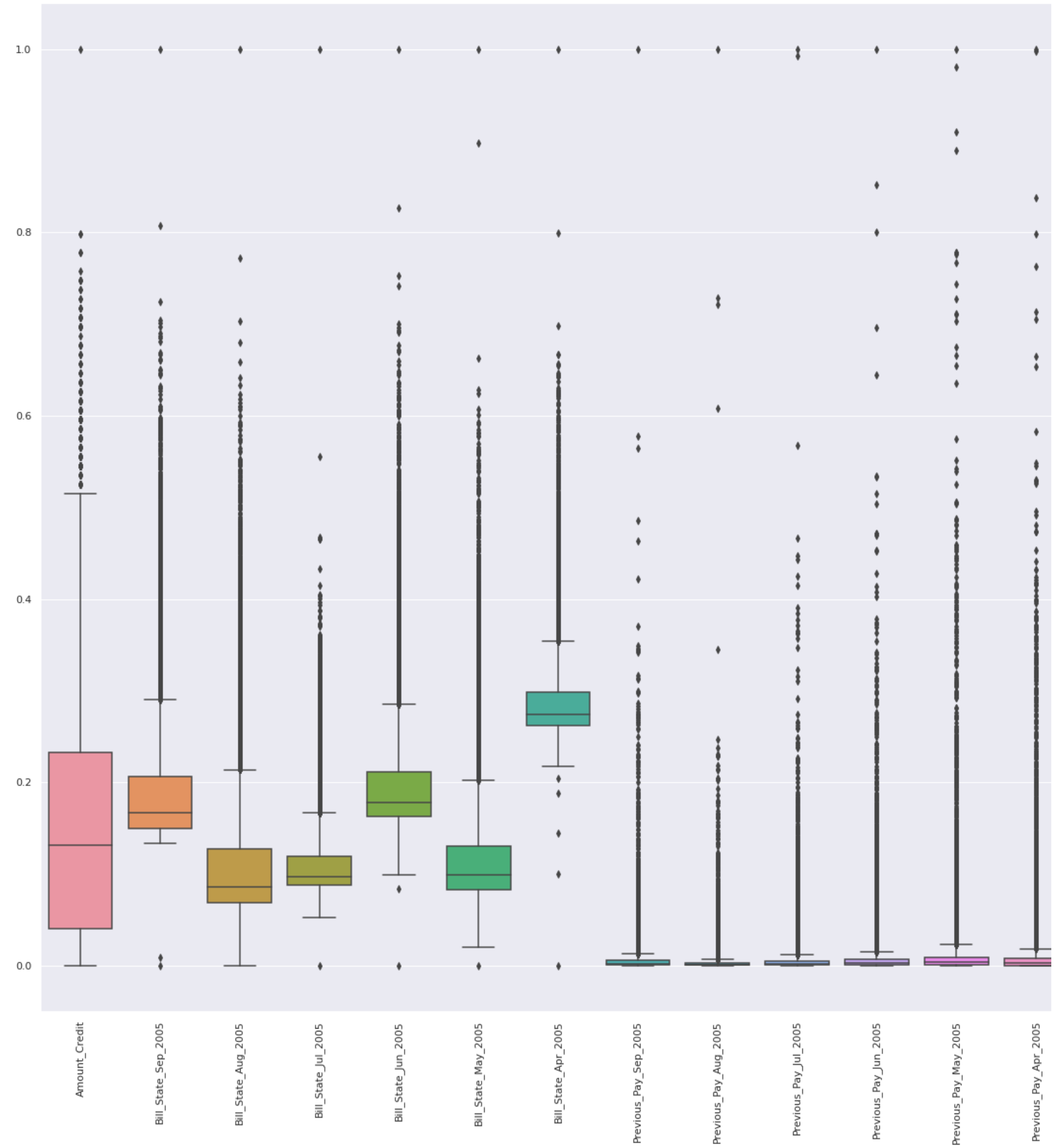
PC12

Grafica 1

```
plt.xticks(rotation = 'vertical')
g = sns.boxplot(data=pcsComponents_df)
```



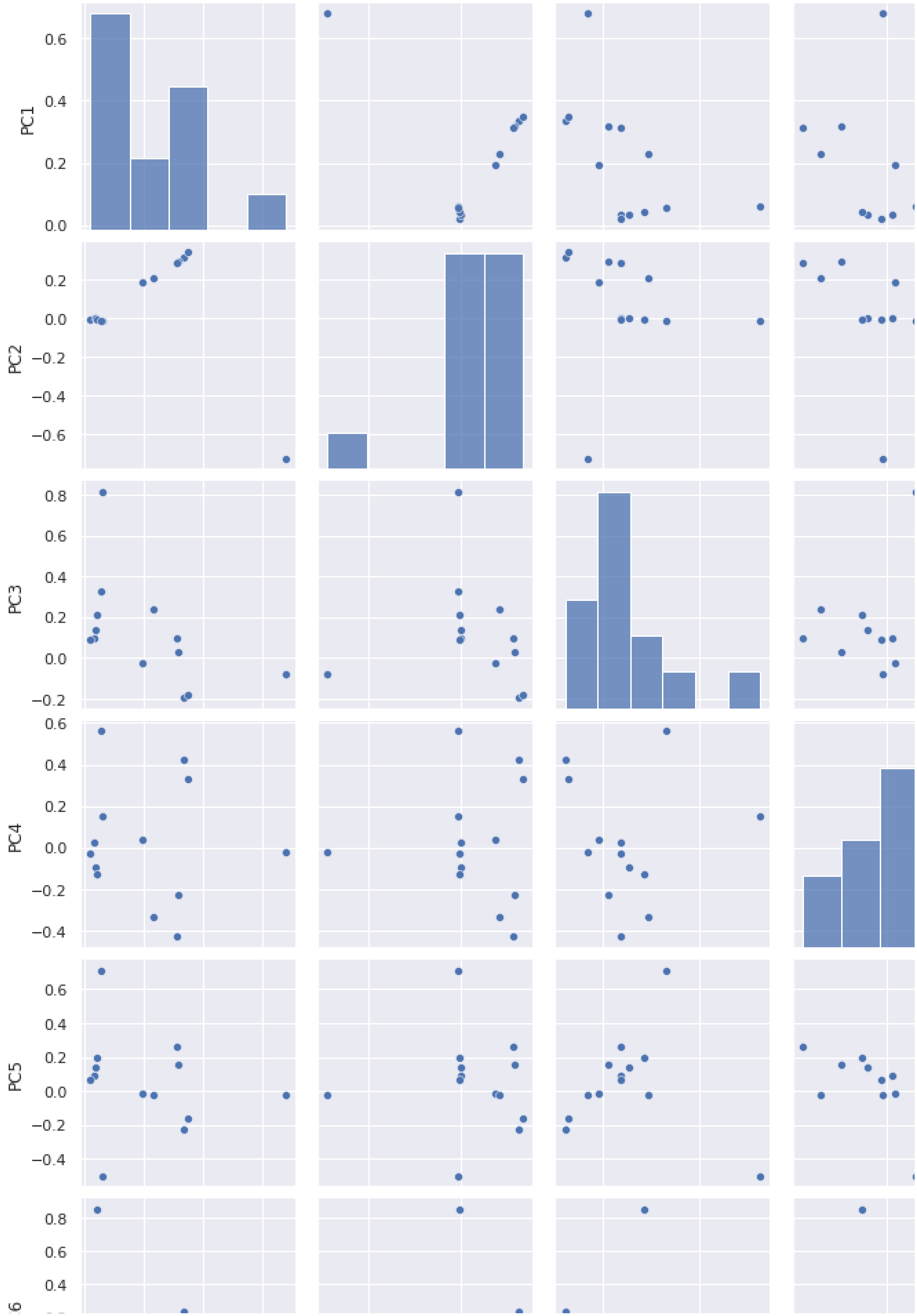

```
plt.xticks(rotation = 'vertical')
g = sns.boxplot(data=scaled_X)
```

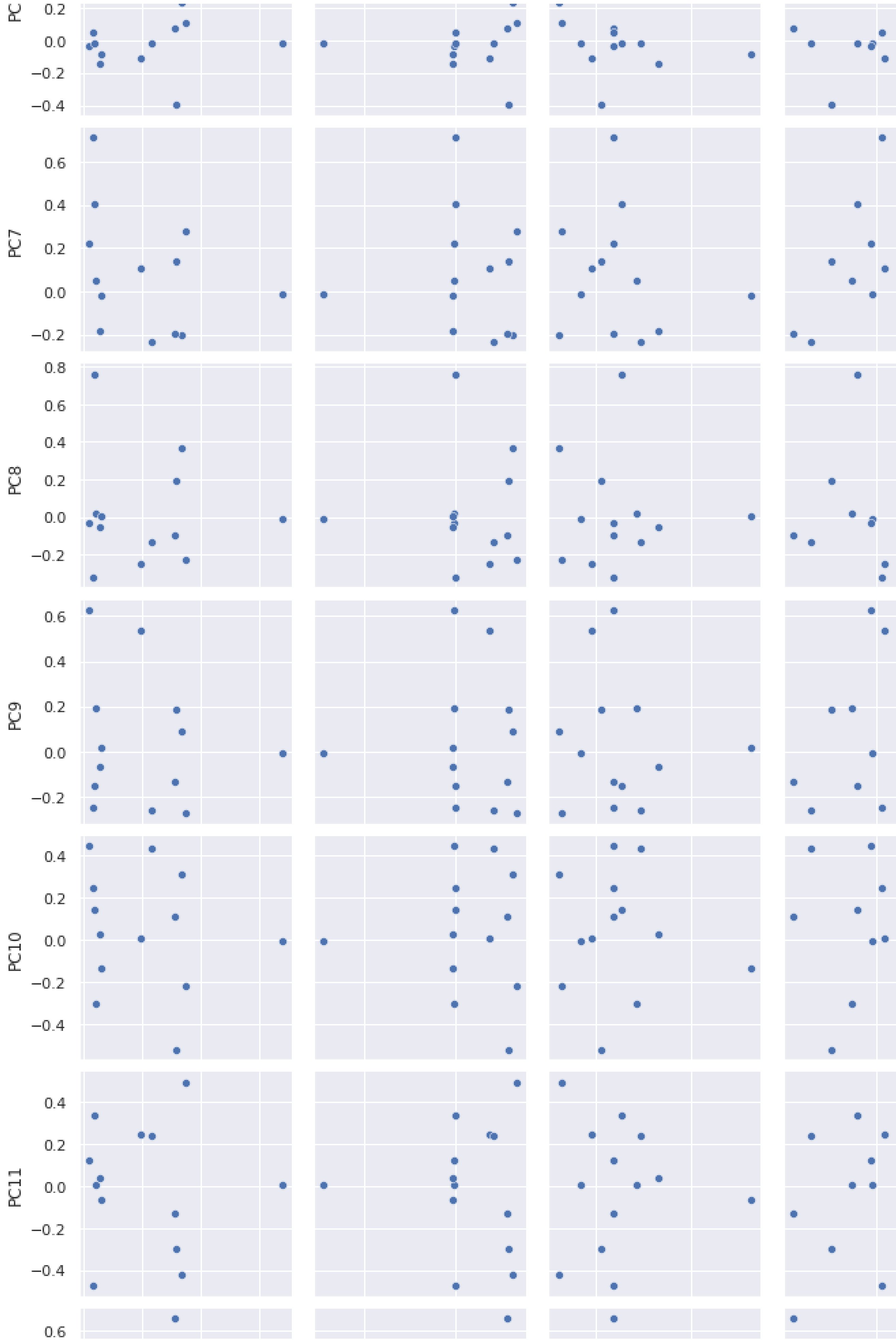


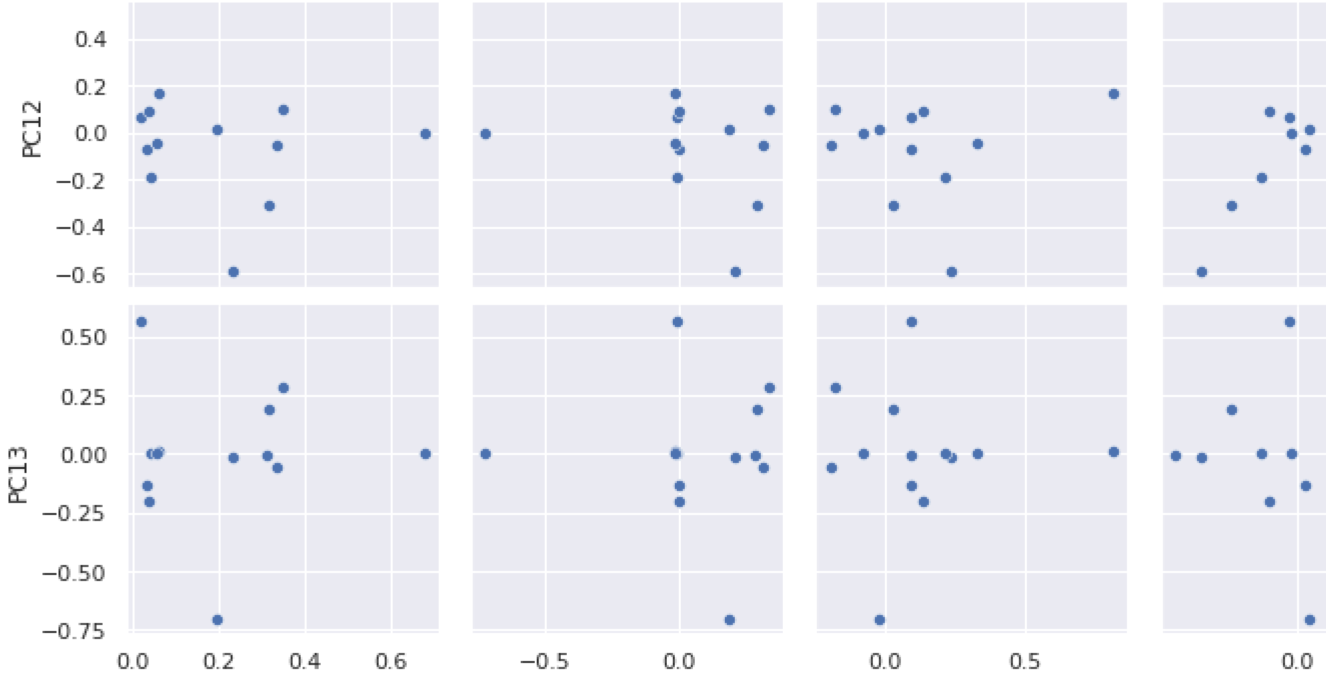
Grafica 2

```
sns.pairplot(pcsComponents_df)
```

```
<seaborn.axisgrid.PairGrid at 0x7fda3a7e3dd0>
```




PC
PC7
PC8
PC9
PC10
PC11




```
sns.pairplot(scaled_X)
```

<seaborn.axisgrid.PairGrid at 0x7fda34f1ad50>

Grafica 3

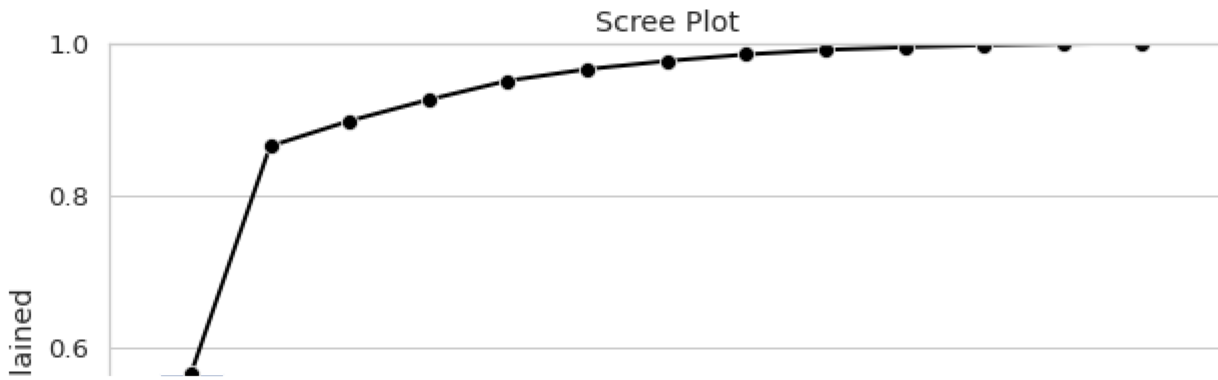
```
PC_components = np.arange(pcs.n_components_) + 1

_ = sns.set(style = 'whitegrid',
            font_scale = 1.2
            )
#### c. Gráfica 3
fig, ax = plt.subplots(figsize=(10, 7))

_ = sns.barplot(x = PC_components,
                y = pcs.explained_variance_ratio_,
                color = 'b'
                )

_ = sns.lineplot(x = PC_components-1,
                 y = np.cumsum(pcs.explained_variance_ratio_),
                 color = 'black',
                 linestyle = '-',
                 linewidth = 2,
                 marker = 'o',
                 markersize = 8
                 )

plt.title('Scree Plot')
plt.xlabel('N-th Principal Component')
plt.ylabel('Variance Explained')
plt.ylim(0, 1)
plt.show()
```



10. Interpreta y explica cada uno de los graficos

Diagrama Boxplot

Con este diagrama podemos observar la distribucion de cada elemento, observando el sesgo que presentan estas mismas, siendo positivos o negativos. El diagrama consta de 4 cuartiles, distribuidos en una caja dividida y dos bigote.

en el primer boxplot nos enfocamos en el PCA, donde pordemos observar que los Componente 7, 10 y 11 son los que presentan una mayor varianza pero sin presentar outliers. Por el otro lado el componente 13 tiene una caja y bigotes reducida, pero con una gran cantidad de outliers.

En el segundo box plot se muestran las columnas y su distribucion, lo que nos permite ver el comportamiento mes a mes de cada variable, lo que nos podria ayudar a detectar anomalias en algun mes en especifico.

Diagrama Pairplot

El pairplot nos permite observar el comportamiento que presentan las variables con respecto a las componentes. Nos permiten visualizar como se correlacionan entre si, o en otras palabras, como las variables forman parte del PC.

Diagrama Scree Plot

Esta ultima grafica nos despliega la varianza explicada, las barras es la varianza de cada una de las componentes, miesntras que la grafica de linea nos muestra la varianza acumulada. Visualmente, podemos observar que sobrepasamos el 90% de la variacion total en la componente PC4. Tambien podemos observar que las componentes que mas aportan a la variacion son las dos primeras.

Esta gráfica es de gran utilidad para determinar el numero minimo de componentes, dependiendo de la varianza acumulada que se este buscando, en este caso con las primeras dos PC ya tenemos mas del 70% explicado.

https://colab.research.google.com/drive/1fjr0cUbJTr98IXqJor7X3rWS4iUuukY7#scrollTo=F-B7uQsjv7uL

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