ACTIVIDAD SEMANA 4

Ciencia y Analítica de Datos

Equipo 170

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Abrimos y leemos el archivo con la base de datos

```
import pandas as pd                          #Importamos·librerias
import·numpy·as·np
import·seaborn·as·sns
from·sklearn.decomposition·import·PCA
import·matplotlib·as·mpl
import·matplotlib.pyplot·as·plt


inPath = 'https://raw.githubusercontent.com/PosgradoMNA/Actividades_Aprendizaje-/main/default


df_credit = pd.read_csv(inPath)         #Leemos el contenido del archivo y lo almacenamos en
df = df_credit.copy()                   #Creamos copia del dataframe
```

Renombramos las columnas para identificar fácilmente las variables categóricas

```
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
        )
```

Ahora intentamos definir cuales son las variables categóricas usando df.info(), sin embargo al ejecutarlo, observamos que todos los datos son de tipo entero y flotante.

Para saber cuales son categóricas nos valdremos de la descripción de la base de datos.

```
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
```

Después de leer y analizar las descripciones, determinamos que las siguientes columnas son categoricas:

Gender, Education, Marital status, Age, Payment september - April 2005

ya que sabemos cuales son las variables categóricas, procedemos a eliminar las variables categóricas, puesto que solo nos interesan las numéricas

```
df = df.drop(['ID', 'Gender', 'Education', 'Marital_Status', 'Age', 'Payment_Sep_2005', 'Paym
```

```
df                  #Dataframe resultante solo con variables numericas
```

	Amount_Credit	Bill_State_Sep_2005	Bill_State_Aug_2005	Bill_State_Jul_20
0	20000	3913.0	3102.0	689
1	120000	2682.0	1725.0	2682
2	90000	29239.0	14027.0	13559
3	50000	46990.0	48233.0	49291
4	50000	8617.0	5670.0	35835
...	...	...	...	
29995	220000	188948.0	192815.0	208365
29996	150000	1683.0	1828.0	3502
29997	30000	3565.0	3356.0	2758
29998	80000	-1645.0	78379.0	76304
29999	50000	47929.0	48905.0	49764

30000 rows × 13 columns

Verificamos la existencia de datos nulos en el dataframe y los eliminamos

```
df.isna().values.any()     #True = Si hay valores nulos
```

```
True
```

```
df.dropna(inplace = True)  #Eliminamos los datos NaN
df.isna().values.any()     #False = No hay datos nulos
```

    False

```
df                  #Dataframe resultante sin datos vacios o nulos
```

	Amount_Credit	Bill_State_Sep_2005	Bill_State_Aug_2005	Bill_State_Jul_20
0	20000	3913.0	3102.0	689
1	120000	2682.0	1725.0	2682
2	90000	29239.0	14027.0	13559
3	50000	46990.0	48233.0	49291
4	50000	8617.0	5670.0	35835
...	...	...	...	
29995	220000	188948.0	192815.0	208365
29996	150000	1683.0	1828.0	3502
29997	30000	3565.0	3356.0	2758
29998	80000	-1645.0	78379.0	76304
29999	50000	47929.0	48905.0	49764

29974 rows × 13 columns

Vemos que los datos que se eliminaron fueron solo 26 lo que representan el 0.08% de los datos.

Así que esto no nos debería afectarnos

```
df.shape    #Mostramos el tamaño del dataframe
```

    (29974, 13)

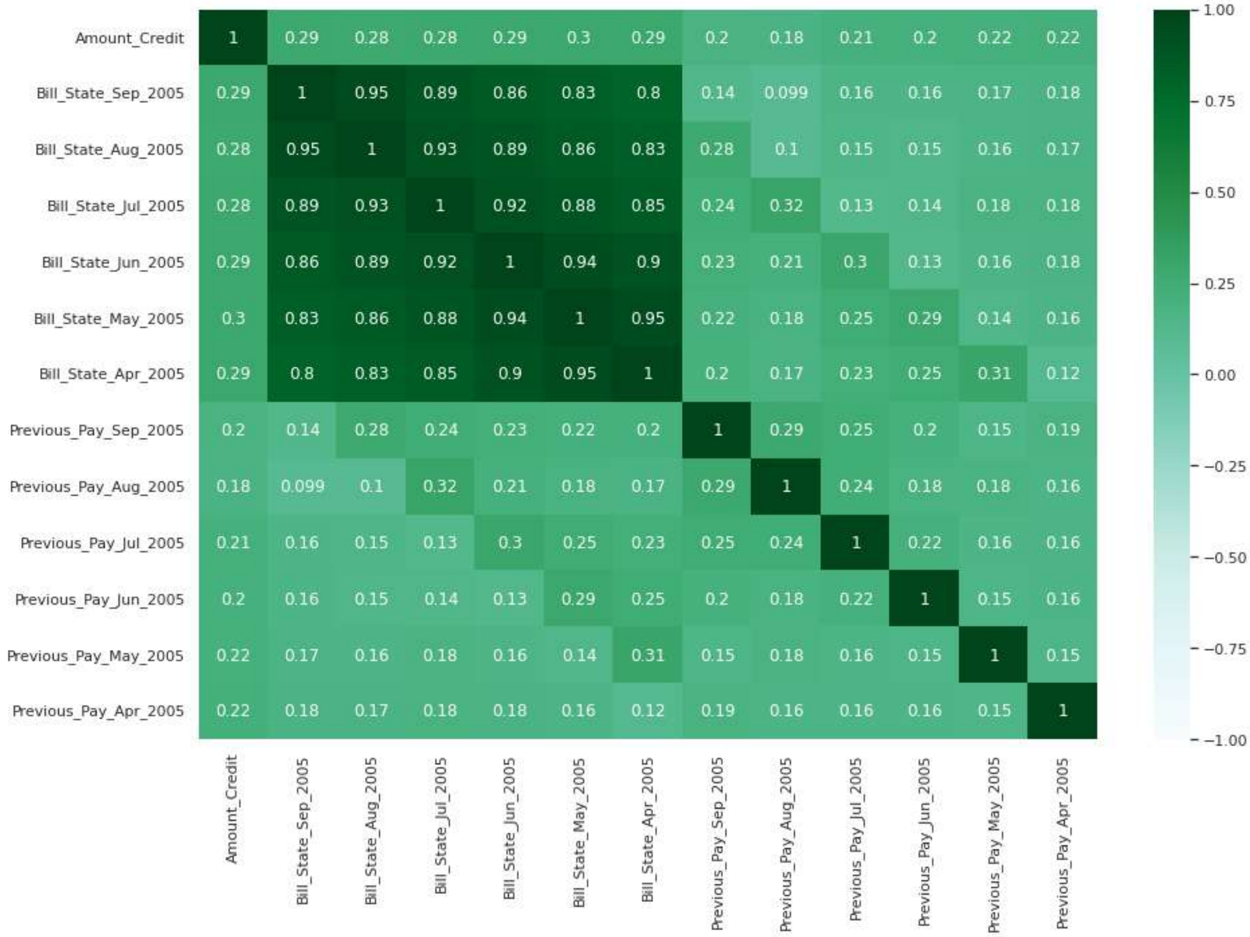
Procedemos a mostrar la correlacion del dataframe resultante

```
df.corr()
```

```
corrs = df.corr()
```

```
sns.set(rc = {'figure.figsize':(15,10)})
sns.heatmap(corrs, vmin = -1, vmax = 1, cmap = "BuGn", annot= True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcd3f6b9f50>
```



Normalización y PCA

Ahora escogemos 2 variables con alta correlación como lo son:

Bill_State_Sep_2005 y Bill_State_Aug_2005 para mostrar sus varianzas

```
ndf = df[['Bill_State_Sep_2005', 'Bill_State_Aug_2005']]
ndf.corr()
```

	Bill_State_Sep_2005	Bill_State_Aug_2005
Bill_State_Sep_2005	1.00000	0.95149
Bill_State_Aug_2005	0.95149	1.00000

```
df.Bill_State_Aug_2005.mean().round(2)
```

```
49202.81
```

```
df.Bill_State_Sep_2005.mean().round(2)
```

```
51246.91
```

```
Varience = np.cov([df.Bill_State_Aug_2005, df.Bill_State_Sep_2005])
Varience
```

```
array([[5.06910390e+09, 4.99000182e+09],
       [4.99000182e+09, 5.42577907e+09]])
```

```
varBillAug =Varience[0][0]
varBillSep = Varience[1][1]
t= ndf.var().sum()


print('Total Varience \t\t\t:', t.round(2) )
print('Varience prop. of Bill State Aug 2005 \t:', ((varBillAug/t)*100).round(2),'%' )
print('Varience prop. of Bill State Sep 2005 \t:', ((varBillSep/t)*100).round(2),'%' )
```

```
Total Varience                      : 10494882969.67
Varience prop. of Bill State Aug 2005   : 48.3 %
Varience prop. of Bill State Sep 2005   : 51.7 %
```

Podemos observar que el rango de valores de la cantidad de Bill State Aug 2005 (48.3%) es menor que la de Bill State Sep 2005 (51.7%), esto no significa que el segundo dato sea mas relevante.

Ahora que sabemos que las varianzas deben igualarse (escalarse).

Escalamos los datos para realizar correctamente el PCA

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled = scaler.fit_transform(df)
scaled_df = pd.DataFrame(scaled, columns=df.columns)
scaled_df.head()
```

	Amount_Credit	Bill_State_Sep_2005	Bill_State_Aug_2005	Bill_State_Jul_2005
0	-1.137194	-0.642612	-0.647516	-0.668120
1	-0.366429	-0.659324	-0.666856	-0.639390
2	-0.597658	-0.298782	-0.494067	-0.482596
3	-0.905965	-0.057792	-0.013622	0.032490
4	-0.905965	-0.578749	-0.611446	-0.161482

```
df_copy = scaled_df.copy()

cols= ['Bill_State_Sep_2005', 'Bill_State_Aug_2005']  #Determinamos las columnas de interes


summary= {"Varianza": df_copy[cols].var()[0:3],    #Imprimimos valores estadisticos
         "Valor Min": df_copy[cols].min()[0:3],
         "Valor Max": df_copy[cols].max()[0:3]
}

pd.DataFrame(summary, index=cols).transpose() #Aplicamos transposicion
```

	Bill_State_Sep_2005	Bill_State_Aug_2005
Varianza	1.000033	1.000033
Valor Min	-2.943672	-1.671148
Valor Max	12.398598	13.128859

```
ndf = df[['Bill_State_Sep_2005', 'Bill_State_Aug_2005']]
ndf.corr()
```

Bill State Sep 2005 Bill State Aug 2005

Aplicamos PCA

Ya que tenemos nuestros datos limpios y escalados, podemos proceder con PCA

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

```
array([[-1.91845082e+00, -4.47427816e-01,  3.72834682e-01, ...,
        -4.68222452e-03,  8.35238023e-03,  1.10229377e-02],
       [-1.70287565e+00, -1.47896759e-01,  5.26159292e-02, ...,
         1.09039897e-02, -3.90155482e-03,  1.78346830e-03],
       [-1.21987458e+00, -2.74742537e-01,  8.94492873e-02, ...,
        -8.05980575e-02, -4.13245461e-02, -5.70550179e-02],
       ...,
       [-1.29095650e+00,  1.39178791e-01,  5.43971037e-01, ...,
         3.51558840e-02,  1.28788803e-02, -1.24710948e-02],
       [ 8.11385979e-01,  2.39953617e+00,  5.31347998e-01, ...,
         1.71849319e-01, -1.40480795e-01, -8.91696233e-03],
       [-5.54537090e-01, -6.80734728e-01,  3.83720867e-01, ...,
        -1.59085563e-02,  1.15150442e-01, -4.84060476e-02]])
```

```
 pcsSummary_df = pd.DataFrame({ '% varianza Explicada': np.round(pcs.explained_variance_ratio
                                '% varianza Acumulada': np.cumsum(pcs.explained_variance_rati
                              })
pcsSummary_df
```

	% varianza Explicada	% varianza Acumulada
0	45.49	45.490116
1	13.17	58.663141
2	7.25	65.909112

```
pcs_labels = [f'PC{i + 1}' for i in range(len(scaled_df.columns))]
pcsSummary_df.index = pcs_labels
pcsSummary_df
```

	% varianza Explicada	% varianza Acumulada
PC1	45.49	45.490116
PC2	13.17	58.663141
PC3	7.25	65.909112
PC4	6.80	72.708324
PC5	6.72	79.427722
PC6	6.02	85.445173
PC7	5.70	91.142604
PC8	5.59	96.729579
PC9	2.03	98.764139
PC10	0.55	99.310418
PC11	0.32	99.626285
PC12	0.19	99.821212
PC13	0.18	100.000000

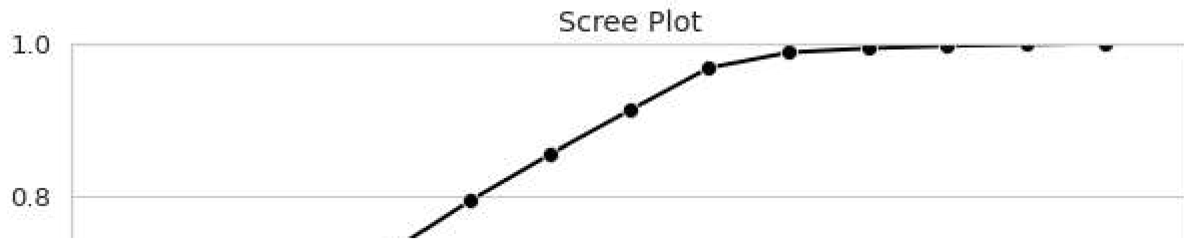
```
pcsSummary_df = pcsSummary_df.transpose()
pcsSummary_df.columns = ['PC{}'.format(i) for i in range(1, len(pcsSummary_df.columns) + 1)]
pcsSummary_df.round(4)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
% varianza Explicada	45.4900	13.1700	7.2500	6.8000	6.7200	6.0200	5.7000	5.5900

```
pcs_df = pd.DataFrame(pcs_t, columns = pcs_labels)

print("Varianza total variables originales:", scaled_df.var().sum())
print("Varianza total de los componentes:", pcs_df.var().sum())
```

```
Varianza total variables originales: 13.00043372368465
Varianza total de los componentes: 13.000433723684635
```

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

_ = sns.set(style = 'whitegrid',
            font_scale = 1.2
            )

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()
```




```
pcs.components_.round(4)
```

```
array([[ 1.648e-01,  3.727e-01,  3.835e-01,  3.885e-01,  3.918e-01,
         3.888e-01,  3.810e-01,  1.352e-01,  1.168e-01,  1.281e-01,
         1.169e-01,  1.138e-01,  1.055e-01],
       [ 2.941e-01, -1.908e-01, -1.741e-01, -1.259e-01, -1.192e-01,
        -1.046e-01, -9.280e-02,  3.861e-01,  4.115e-01,  3.947e-01,
         3.519e-01,  3.056e-01,  3.252e-01],
       [-3.931e-01, -7.450e-02,  3.500e-03,  7.240e-02,  8.080e-02,
         5.070e-02, -4.460e-02,  3.935e-01,  4.110e-01,  2.656e-01,
        -5.240e-02, -5.337e-01, -3.764e-01],
       [ 5.020e-02,  4.050e-02,  8.420e-02,  1.115e-01,  3.090e-02,
        -1.024e-01, -1.721e-01,  2.364e-01,  1.447e-01, -2.241e-01,
        -5.684e-01, -2.470e-01,  6.513e-01],
       [-1.037e-01, -3.880e-02, -2.530e-02,  1.018e-01,  1.130e-02,
        -1.034e-01,  6.980e-02,  3.270e-02,  3.979e-01, -1.340e-01,
        -5.049e-01,  6.393e-01, -3.465e-01],
       [ 2.557e-01,  3.200e-03, -3.310e-02, -1.156e-01,  1.221e-01,
        -1.400e-02, -5.000e-03, -1.787e-01, -2.517e-01,  7.522e-01,
        -4.874e-01, -4.310e-02, -6.730e-02],
       [-8.000e-01,  1.780e-02, -1.340e-02, -2.540e-02,  4.540e-02,
         3.480e-02,  6.540e-02, -1.705e-01, -7.210e-02,  2.852e-01,
         5.780e-02,  2.538e-01,  4.099e-01],
       [ 1.094e-01,  6.700e-03, -1.361e-01,  9.680e-02,  3.330e-02,
         4.400e-02, -1.210e-02, -7.351e-01,  5.952e-01,  2.890e-02,
         6.110e-02, -2.129e-01,  1.114e-01],
       [-3.110e-02,  5.667e-01,  3.868e-01,  1.229e-01, -2.053e-01,
        -4.200e-01, -4.888e-01, -5.650e-02,  5.090e-02,  1.450e-01,
         1.242e-01,  6.020e-02, -9.890e-02],
       [-6.100e-03,  4.160e-01,  3.840e-02, -4.847e-01, -5.232e-01,
         6.820e-02,  5.135e-01,  4.760e-02,  1.473e-01,  2.000e-04,
        -1.158e-01, -9.950e-02,  3.500e-02],
       [ 1.550e-02, -4.330e-01,  3.448e-01,  4.960e-01, -4.895e-01,
        -2.497e-01,  3.387e-01, -6.930e-02, -6.890e-02,  1.247e-01,
         1.100e-03, -6.940e-02,  2.770e-02],
       [-4.000e-04, -1.838e-01,  3.297e-01, -8.650e-02, -3.623e-01,
         7.183e-01, -4.275e-01, -4.490e-02,  3.900e-02,  2.550e-02,
        -8.070e-02,  9.520e-02, -1.720e-02],
       [ 3.500e-03, -3.166e-01,  6.452e-01, -5.276e-01,  3.461e-01,
        -2.268e-01,  7.240e-02, -8.460e-02,  1.249e-01, -6.310e-02,
         4.230e-02, -8.600e-03,  8.300e-03]])
```

```
pcsComponents_df = pd.DataFrame(pcs.components_.transpose(),
                                columns=pcs_df.columns,
                                index=df.columns
                                )
pcsComponents_df.iloc[:, :5]
```

	PC1	PC2	PC3	PC4	PC5
Amount_Credit	0.164797	0.294112	-0.393084	0.050175	-0.103697
Bill_State_Sep_2005	0.372671	-0.190750	-0.074463	0.040539	-0.038815
Bill_State_Aug_2005	0.383515	-0.174102	0.003523	0.084170	-0.025290
Bill_State_Jul_2005	0.388535	-0.125858	0.072443	0.111451	0.101761
Bill_State_Jun_2005	0.391847	-0.119230	0.080821	0.030852	0.011276
Bill_State_May_2005	0.388801	-0.104601	0.050723	-0.102352	-0.103418
Bill_State_Apr_2005	0.380960	-0.092842	-0.044644	-0.172057	0.069835
Previous_Pay_Sep_2005	0.135177	0.386136	0.393515	0.236365	0.032729
Previous_Pay_Aug_2005	0.116801	0.411454	0.411007	0.144705	0.397852
Previous_Pay_Jul_2005	0.128074	0.394666	0.265639	-0.224095	-0.133951
Previous_Pay_Jun_2005	0.116934	0.351921	-0.052389	-0.568388	-0.504858
Previous_Pay_May_2005	0.113804	0.305641	-0.533664	-0.247007	0.639350
Previous_Pay_Apr_2005	0.105503	0.325212	-0.376425	0.651305	-0.346549