TAREA 4_Auil_Cabezas

December 19, 2022

1 Tarea 4 - Mario Cabezas - Lucas Auil

2 Carga de bibliotecas

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
import sklearn
import scipy
from scipy.linalg import eigh, cholesky
from scipy.stats import norm
import linearmodels.panel as lmp
from pylab import plot, show, axis, subplot, xlabel, ylabel, grid
import semopy
import seaborn as sns
from factor_analyzer import FactorAnalyzer
from sklearn.decomposition import PCA

%matplotlib inline
```

3 Carga y limpieza de datos

Lo primero que realizamos es cargar la data a trabajar que en este caso es la base de datos llamada junaeb2 , la cual viene en formato csv

[2]:
```
Xr = pd.read_csv('../TAREA FINAL/junaeb2.csv')
Xr
```

[2]:
```
      sexo  edad  imce  vive_padre  vive_madre  sk1  sk2  sk3  sk4  sk5  …  \
0        1    85  0.75           1           1    1    1    1    2    1  …
1        0    76  0.71           0           1    1    1    1    1    1  …
2        1    68  0.27           0           1    2    2    3    2    1  …
3        1    84  2.05           1           1    1    1    1    1    1  …
4        0    86  1.05           1           1    1    1    1    1    1  …
…      …    …    …            …         …    …    …    …    …    …  …
```

```
59994      0    78   1.63           1            1     1     3     1     2     2   …
59995      1    79   2.57           1            1     1     1     2     2     1   …
59996      0    78   2.12           1            1     1     1     1     1     1   …
59997      1    78  -0.43           1            1     1     1     1     1     2   …
59998      0    78  -0.55           0            1     2     2     1     1     1   …

        sk9  sk10  sk11  sk12  sk13  act_fisica  area  educm  educp  madre_work
0         2     2     2     3     2         NaN     0   11.0     11          -1
1         1     1     1     1     1         5.0     0    8.0      8           1
2         2     3     2     1     3         NaN     1   13.0     13           1
3         1     1     1     1     1         2.0     1   16.0     12          -1
4         1     1     1     1     1         1.0     1   17.0     15           0
…    …    …    …    …    …         …    …    …    …          …
59994     2     2     2     1     1         2.0     1   13.0     13          -1
59995     1     3     2     1     4         3.0     1   18.0     19           0
59996     1     3     1     1     1         3.0     1   13.0      9           1
59997     1     2     1     1     2         2.0     1   17.0     15           1
59998     1     1     1     1     1         1.0     1   18.0     11           1

[59999 rows x 23 columns]
```

Analizando tanto los datos desplegados en python como la base de datos en Excel , nos dimos cuenta que en las variables act_fisica y educm existian datos vacios, por lo que procedimos a eliminar completamente dichas filas de nuestra data

[3]:
```python
Xr.dropna(inplace=True)
Xr.reset_index(drop=True, inplace=True)
Xr
```

[3]:
```
        sexo  edad  imce  vive_padre  vive_madre  sk1  sk2  sk3  sk4  sk5  …  \
0          0    76  0.71           0           1    1    1    1    1    1  …
1          1    84  2.05           1           1    1    1    1    1    1  …
2          0    86  1.05           1           1    1    1    1    1    1  …
3          0    74  1.39           1           1    1    2    1    1    1  …
4          1    91  2.75           1           1    1    1    1    2    2  …
…    …    …    …         …         …   …   …   …   …   …   …
57352      0    78  1.63           1           1    1    3    1    2    2  …
57353      1    79  2.57           1           1    1    1    2    2    1  …
57354      0    78  2.12           1           1    1    1    1    1    1  …
57355      1    78 -0.43           1           1    1    1    1    1    2  …
57356      0    78 -0.55           0           1    2    2    1    1    1  …

        sk9  sk10  sk11  sk12  sk13  act_fisica  area  educm  educp  madre_work
0         1     1     1     1     1         5.0     0    8.0      8           1
1         1     1     1     1     1         2.0     1   16.0     12          -1
2         1     1     1     1     1         1.0     1   17.0     15           0
3         1     1     1     1     1         4.0     0    8.0      8          -1
```

```
4          3     3     3     2     2         2.0     1   20.0     19            1
…     …    …     …     …     …           …     …     …     …          …
57352      2     2     2     1     1         2.0     1   13.0     13           -1
57353      1     3     2     1     4         3.0     1   18.0     19            0
57354      1     3     1     1     1         3.0     1   13.0      9            1
57355      1     2     1     1     2         2.0     1   17.0     15            1
57356      1     1     1     1     1         1.0     1   18.0     11            1

[57357 rows x 23 columns]
```

[4]:
```python
Xr.dtypes
```

[4]:
```
sexo              int64
edad              int64
imce            float64
vive_padre        int64
vive_madre        int64
sk1               int64
sk2               int64
sk3               int64
sk4               int64
sk5               int64
sk6               int64
sk7               int64
sk8               int64
sk9               int64
sk10              int64
sk11              int64
sk12              int64
sk13              int64
act_fisica      float64
area              int64
educm           float64
educp             int64
madre_work        int64
dtype: object
```

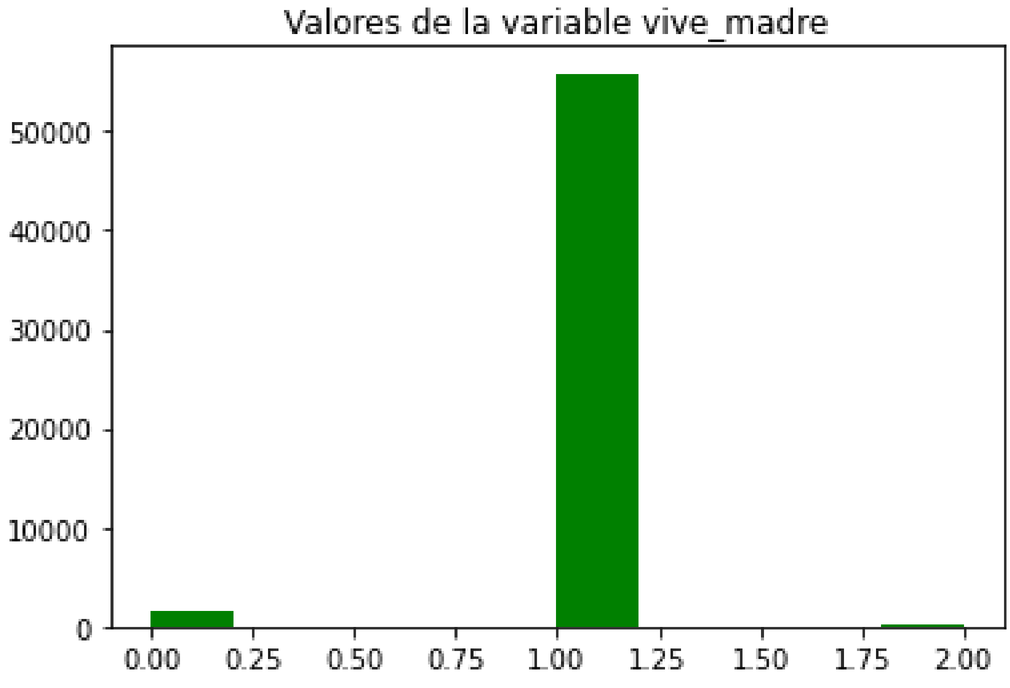
[5]:
```python
Xr["act_fisica"] = Xr["act_fisica"].astype("int64")
Xr["educm"] = Xr["educm"].astype("int64")
Xr.dtypes
```

[5]:
```
sexo              int64
edad              int64
imce            float64
vive_padre        int64
vive_madre        int64
sk1               int64
```

```
sk2             int64
sk3             int64
sk4             int64
sk5             int64
sk6             int64
sk7             int64
sk8             int64
sk9             int64
sk10            int64
sk11            int64
sk12            int64
sk13            int64
act_fisica      int64
area            int64
educm           int64
educp           int64
madre_work      int64
dtype: object
```

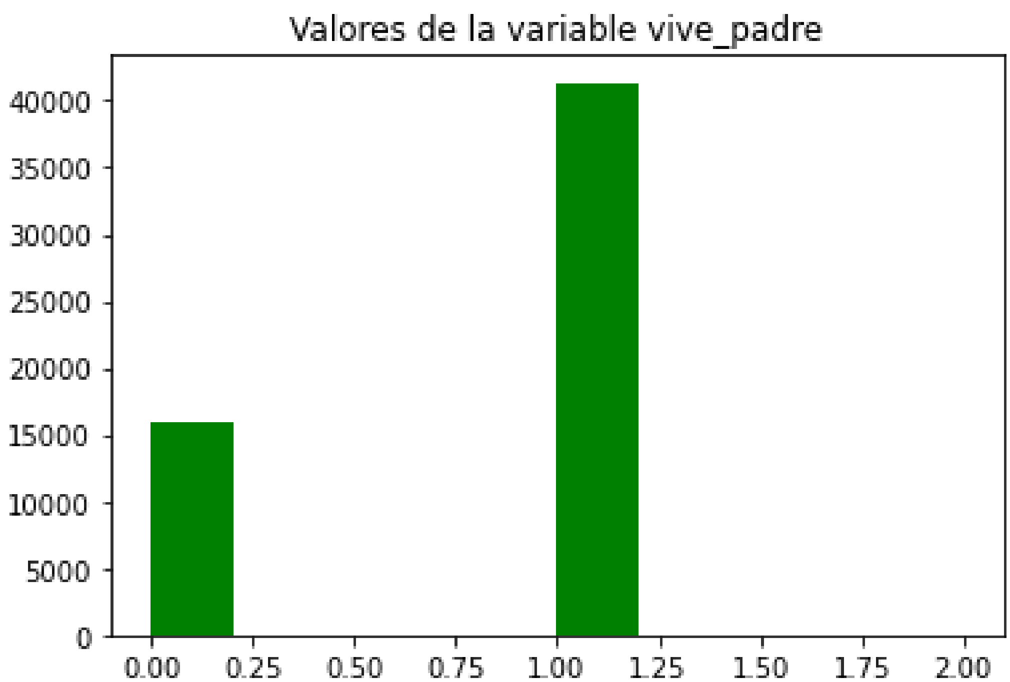
[6]:
```
plt.hist(Xr['vive_madre'],color="green")
plt.title("Valores de la variable vive_madre")
Xr.vive_madre.value_counts()
```

[6]:
```
1    55832
0     1437
2       88
Name: vive_madre, dtype: int64
```



[7]:
```
plt.hist(Xr['vive_padre'],color="green")
plt.title("Valores de la variable vive_padre")
Xr.vive_padre.value_counts()
```

[7]:
```
1    41337
0    15998
2       22
Name: vive_padre, dtype: int64
```



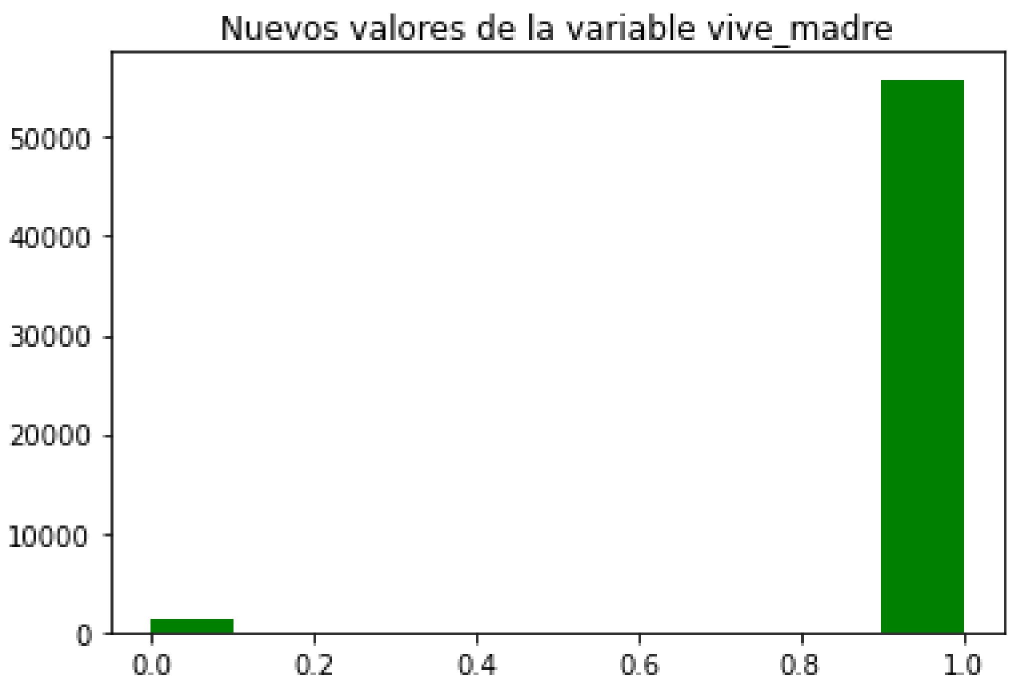
[8]:
```
Xr.drop(Xr[Xr['vive_madre']==2].index,inplace =True)
Xr.drop(Xr[Xr['vive_padre']==2].index,inplace =True)
Xr.reset_index(drop=True, inplace=True)
Xr
```

[8]:
```
       sexo  edad  imce  vive_padre  vive_madre  sk1  sk2  sk3  sk4  sk5  …  \
0         0    76  0.71           0           1    1    1    1    1    1  …
1         1    84  2.05           1           1    1    1    1    1    1  …
2         0    86  1.05           1           1    1    1    1    1    1  …
3         0    74  1.39           1           1    1    2    1    1    1  …
4         1    91  2.75           1           1    1    1    1    2    2  …
…       …     …     …           …           …    …    …    …    …    …  …
57242     0    78  1.63           1           1    1    3    1    2    2  …
```

```
57243      1     79   2.57            1            1     1     1     2     2     1  …
57244      0     78   2.12            1            1     1     1     1     1     1  …
57245      1     78  -0.43            1            1     1     1     1     1     2  …
57246      0     78  -0.55            0            1     2     2     1     1     1  …

       sk9  sk10  sk11  sk12  sk13  act_fisica  area  educm  educp  madre_work
0        1     1     1     1     1           5     0      8      8           1
1        1     1     1     1     1           2     1     16     12          -1
2        1     1     1     1     1           1     1     17     15           0
3        1     1     1     1     1           4     0      8      8          -1
4        3     3     3     2     2           2     1     20     19           1
…     …    …    …    …    …         …    …     …      …           …
57242    2     2     2     1     1           2     1     13     13          -1
57243    1     3     2     1     4           3     1     18     19           0
57244    1     3     1     1     1           3     1     13      9           1
57245    1     2     1     1     2           2     1     17     15           1
57246    1     1     1     1     1           1     1     18     11           1

[57247 rows x 23 columns]
```

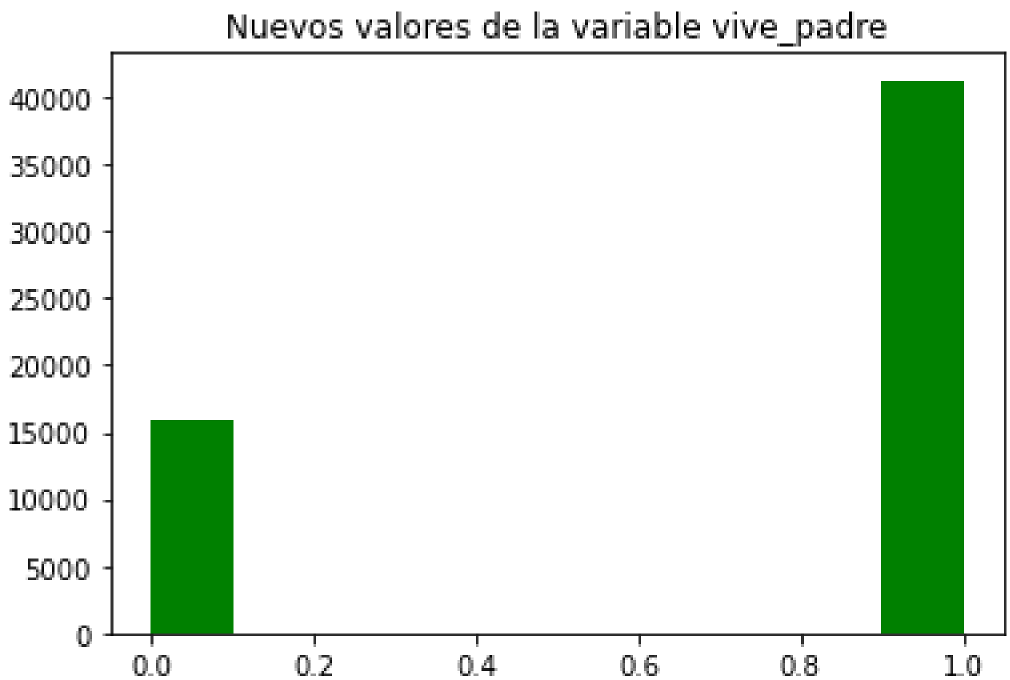
[9]:
```python
plt.hist(Xr['vive_madre'],color="green")
plt.title("Nuevos valores de la variable vive_madre")
Xr.vive_madre.value_counts()
```

[9]:
```
1    55828
0     1419
Name: vive_madre, dtype: int64
```



[10]:
```
plt.hist(Xr['vive_padre'],color="green")
plt.title("Nuevos valores de la variable vive_padre")
Xr.vive_padre.value_counts()
```

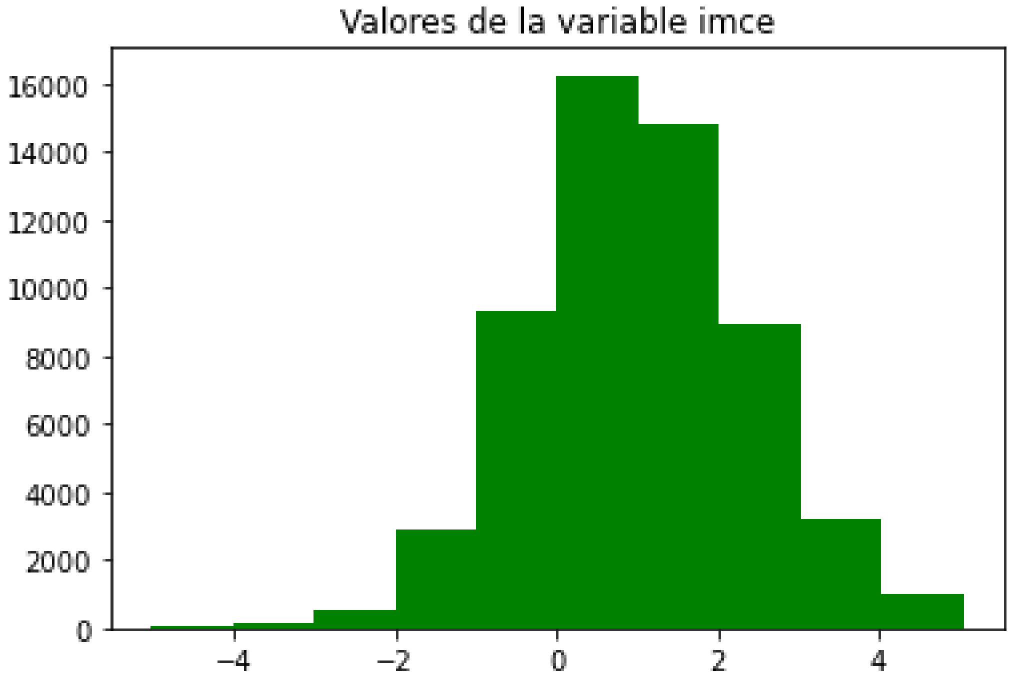
[10]:
```
1    41280
0    15967
Name: vive_padre, dtype: int64
```



[11]:
```
plt.hist(Xr['imce'],color="green")
plt.title("Valores de la variable imce")
Xr.imce.value_counts()
```

[11]:
```
 0.74    208
 1.07    197
 0.87    197
 0.73    195
 0.39    195
        …
-3.35      1
-4.36      1
-4.66      1
-3.17      1
```

```
-4.88      1
Name: imce, Length: 928, dtype: int64
```



[12]:
```
Xr.drop(Xr[Xr['imce']<0].index,inplace =True)
Xr.reset_index(drop=True, inplace=True)
Xr
```

[12]:
```
       sexo  edad  imce  vive_padre  vive_madre  sk1  sk2  sk3  sk4  sk5  …  \
0         0    76  0.71           0           1    1    1    1    1    1  …
1         1    84  2.05           1           1    1    1    1    1    1  …
2         0    86  1.05           1           1    1    1    1    1    1  …
3         0    74  1.39           1           1    1    2    1    1    1  …
4         1    91  2.75           1           1    1    1    1    2    2  …
…       …     …     …           …           …    …    …    …    …    …  …
44497     1    78  1.58           1           1    1    1    1    1    1  …
44498     1    79  1.73           1           0    1    1    2    1    1  …
44499     0    78  1.63           1           1    1    3    1    2    2  …
44500     1    79  2.57           1           1    1    1    2    2    1  …
44501     0    78  2.12           1           1    1    1    1    1    1  …

       sk9  sk10  sk11  sk12  sk13  act_fisica  area  educm  educp  madre_work
0        1     1     1     1     1           5     0      8      8           1
1        1     1     1     1     1           2     1     16     12          -1
2        1     1     1     1     1           1     1     17     15           0
```

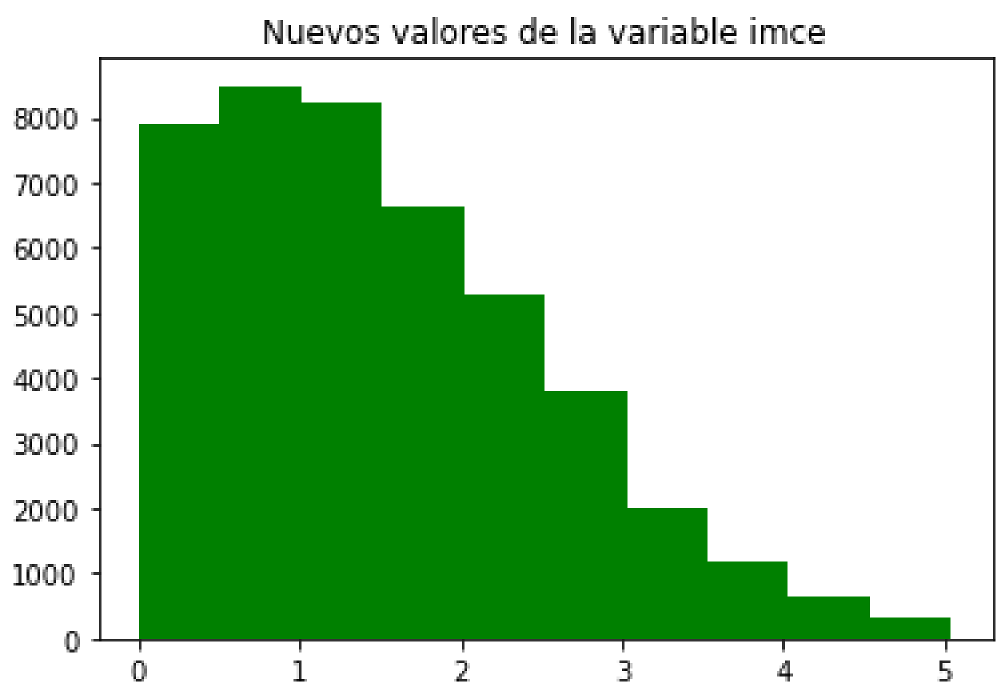
```
3         1      1      1      1      1           4      0      8      8          -1
4         3      3      3      2      2           2      1     20     19           1
…     …   …   …   …   …         …   …   …   …         …
44497     1      4      3      3      5           1      0     13     12          -1
44498     1      1      2      1      2           2      1     17     17           1
44499     2      2      2      1      1           2      1     13     13          -1
44500     1      3      2      1      4           3      1     18     19           0
44501     1      3      1      1      1           3      1     13      9           1

[44502 rows x 23 columns]
```

[13]:

```
plt.hist(Xr['imce'],color="green")
plt.title("Nuevos valores de la variable imce")
Xr.imce.value_counts()
```

[13]:

```
0.74    208
1.07    197
0.87    197
0.39    195
0.73    195
       ...
5.02      3
4.93      3
4.82      2
5.00      2
4.89      2
Name: imce, Length: 505, dtype: int64
```

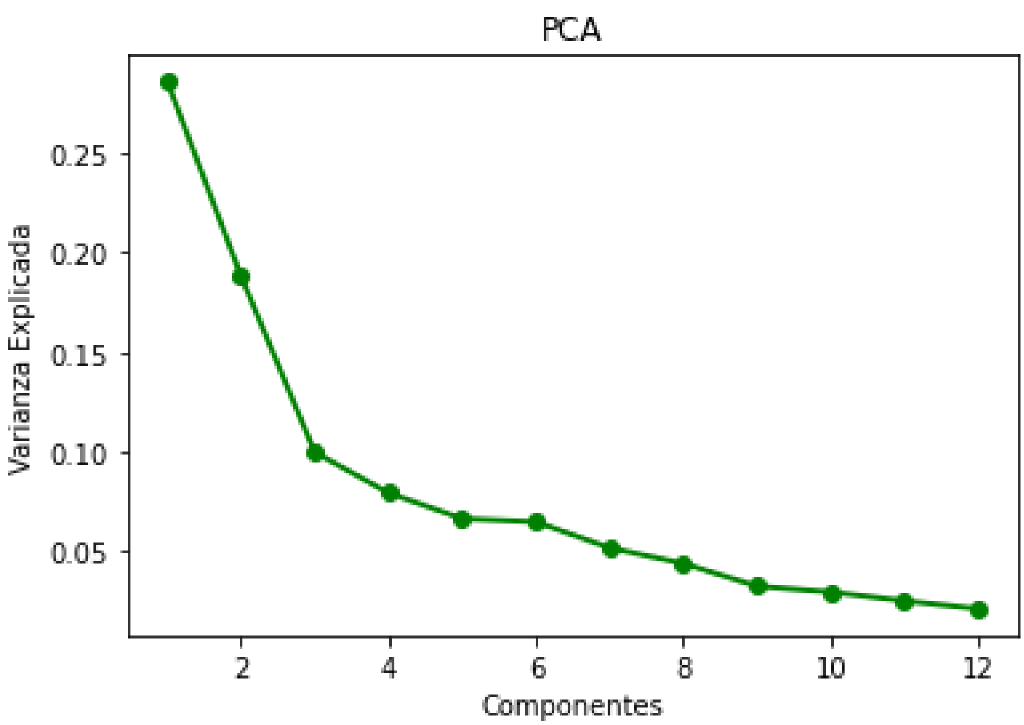


4 1 PCA

[14]:
```
vector_sks =␣
 ↪Xr[["sk1","sk2","sk3","sk4","sk5","sk6","sk7","sk8","sk9","sk10","sk11","sk12","sk13"]]
pca = PCA(n_components=12)
pca_features = pca.fit_transform(vector_sks)
print(pca.explained_variance_ratio_)
```

```
[0.28606755 0.18817514 0.09973579 0.07929705 0.06632621 0.06471883
 0.05164867 0.0437851  0.03238106 0.0294521  0.02499784 0.02101661]
```

[15]:
```
PC_values = np.arange(pca.n_components_) + 1
plt.plot(PC_values, pca.explained_variance_ratio_, 'o-', linewidth=2,␣
 ↪color='green')
plt.title('PCA')
plt.xlabel('Componentes')
plt.ylabel('Varianza Explicada')
plt.show()
```



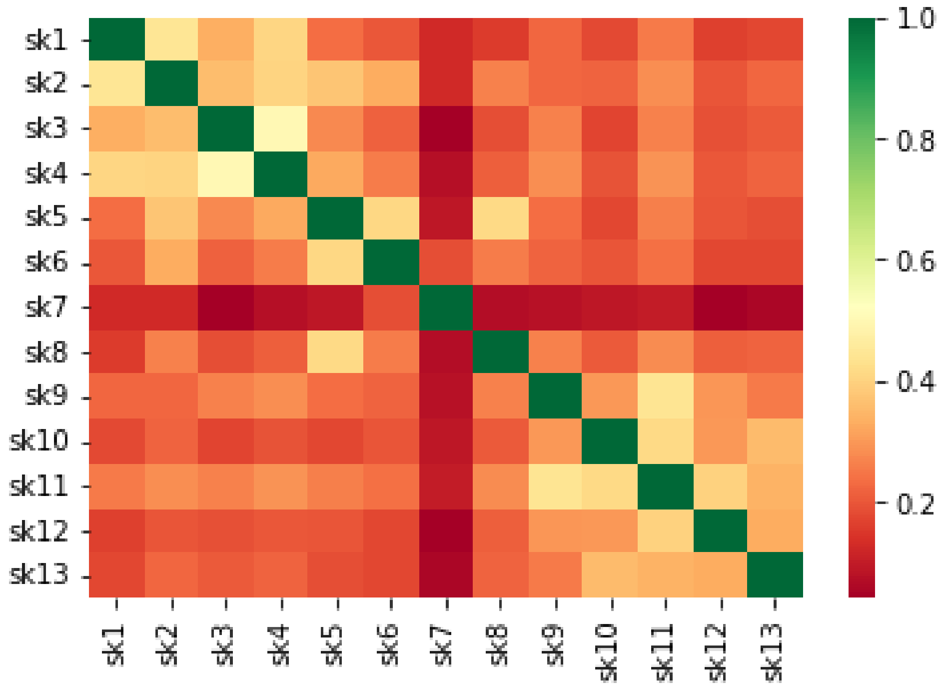
[16]:
```
pca = PCA(n_components='mle')
pca_features = pca.fit_transform(vector_sks)
print(pca.explained_variance_ratio_)
```

```
[0.28606755 0.18817514 0.09973579 0.07929705 0.06632621 0.06471883
 0.05164867 0.0437851  0.03238106 0.0294521  0.02499784 0.02101661]
```

Los valores propios de cada varaible son: [0.28606755 0.18817514 0.09973579 0.07929705 0.06632621 0.06471883 0.05164867 0.0437851 0.03238106 0.0294521 0.02499784 0.02101661]. Además, no fue posible disminuir las variables a un número óptimo, en función de la varianza de los datos, puesto que estas no tenían correlación entre sí.

[17]:
```
sns.heatmap(vector_sks.corr(), cmap='RdYlGn')
```

[17]: <AxesSubplot:>



[18]:
```
pca_vectors = pd.DataFrame(data = pca.components_)
pca_vectors.head()
```

[18]:

	0	1	2	3	4	5	6 \
0	0.101837	0.228681	0.166704	0.180646	0.186154	0.249874	0.351651
1	0.007632	0.034134	0.066008	0.055333	0.040743	-0.028742	-0.923058
2	0.084242	0.266514	0.180453	0.191232	0.300941	0.341428	-0.115066
3	-0.004360	-0.033451	-0.039866	-0.031587	-0.046156	-0.002758	-0.032316
4	0.143585	0.268222	0.309358	0.295992	-0.021423	0.162823	-0.030117

```
          7         8         9        10        11        12
0  0.291481  0.234854  0.406509  0.282787  0.293839  0.429516
1  0.099394  0.086327  0.168557  0.104073  0.155922  0.236538
2  0.477371  0.079394 -0.373427  0.000937 -0.089114 -0.500784
3 -0.095896  0.105624  0.707258  0.138852  0.022035 -0.672875
4 -0.746663  0.111445 -0.196699  0.105288  0.259159 -0.096871
```

[19]:

```
pca_df = pd.DataFrame(data=pca_features,columns=['PC1', 'PC2',␣
↪'PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11','P12'])
pca_df.describe().apply(lambda s: s.apply('{0:.3f}'.format))
```

[19]:

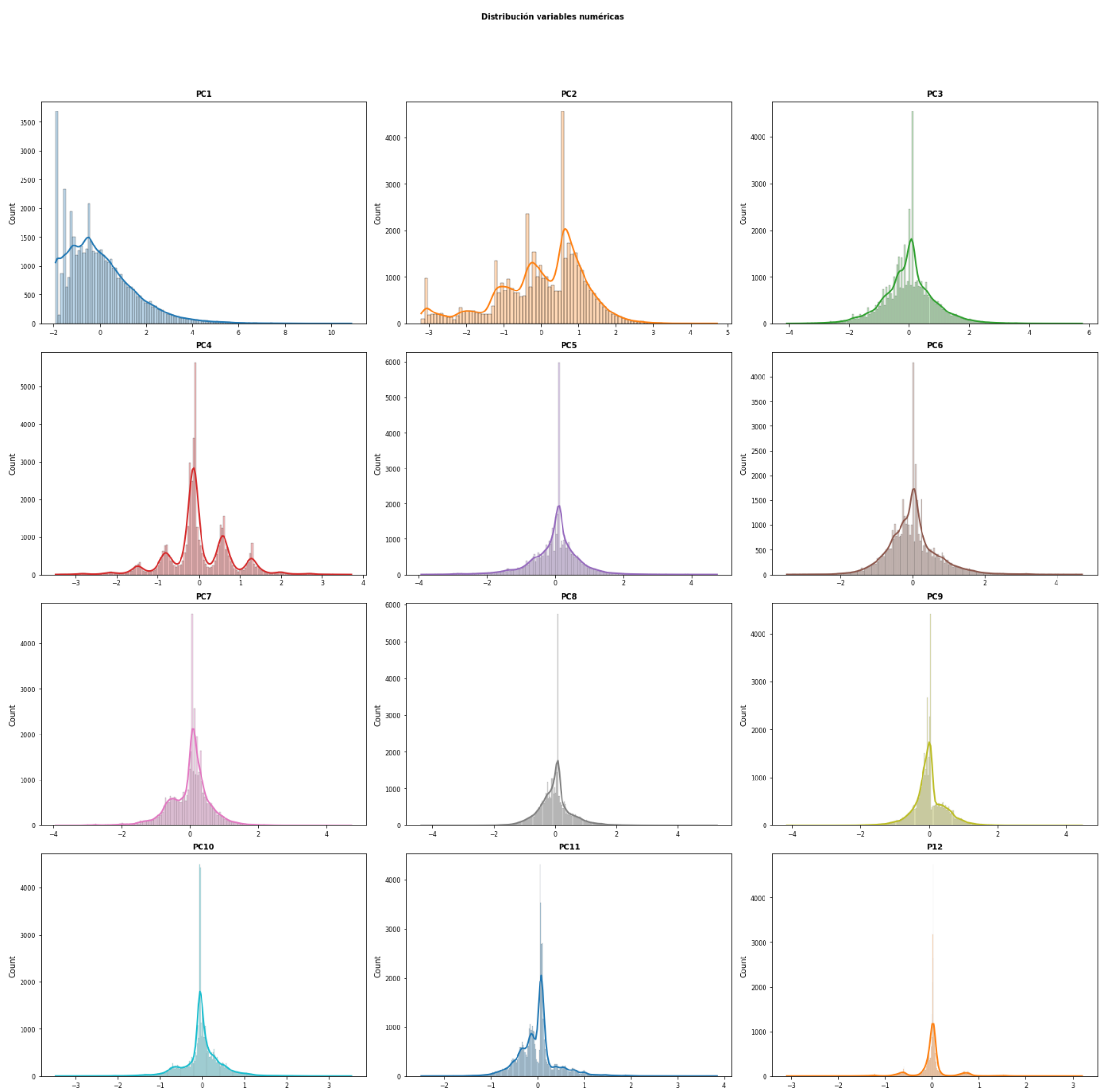
```
             PC1        PC2        PC3        PC4        PC5        PC6  \
count  44502.000  44502.000  44502.000  44502.000  44502.000  44502.000
mean       0.000      0.000     -0.000     -0.000     -0.000     -0.000
std        1.464      1.187      0.864      0.771      0.705      0.696
min       -1.910     -3.208     -4.086     -3.485     -3.926     -3.496
25%       -1.100     -0.714     -0.465     -0.255     -0.299     -0.400
50%       -0.260      0.185     -0.002     -0.097      0.094      0.018
75%        0.790      0.809      0.454      0.514      0.346      0.283
max       10.878      4.703      5.779      3.710      4.752      4.718

             PC7        PC8        PC9       PC10       PC11        P12
count  44502.000  44502.000  44502.000  44502.000  44502.000  44502.000
mean       0.000      0.000     -0.000      0.000     -0.000     -0.000
std        0.622      0.573      0.492      0.470      0.433      0.397
min       -3.943     -4.363     -4.163     -3.469     -2.495     -3.101
25%       -0.311     -0.289     -0.212     -0.116     -0.221     -0.062
50%        0.065      0.026     -0.016     -0.038      0.051      0.021
75%        0.315      0.191      0.202      0.189      0.113      0.047
max        4.730      5.275      4.471      3.543      3.841      3.208
```

En las siguientes gráficas se puede observar la distribución de cada componente

[20]:

```
fig, axes = plt.subplots(nrows=4, ncols=3, figsize=(20, 20))
axes = axes.flat
columnas_numeric = pca_df.select_dtypes(include=['float64', 'int']).columns



for i, colum in enumerate(columnas_numeric):
        sns.histplot(
            data     = pca_df,
            x        = colum,
            stat     = "count",
            kde      = True,
            color    = (list(plt.rcParams['axes.prop_cycle'])*2)[i]["color"],
```

```
            line_kws= {'linewidth': 2},
            alpha    = 0.3,
            ax       = axes[i]
        )
        axes[i].set_title(colum, fontsize = 10, fontweight = "bold")
        axes[i].tick_params(labelsize = 8)
        axes[i].set_xlabel("")




fig.tight_layout()
plt.subplots_adjust(top = 0.9)
fig.suptitle('Distribución variables numéricas', fontsize = 10, fontweight =␣
 ↪"bold");
```

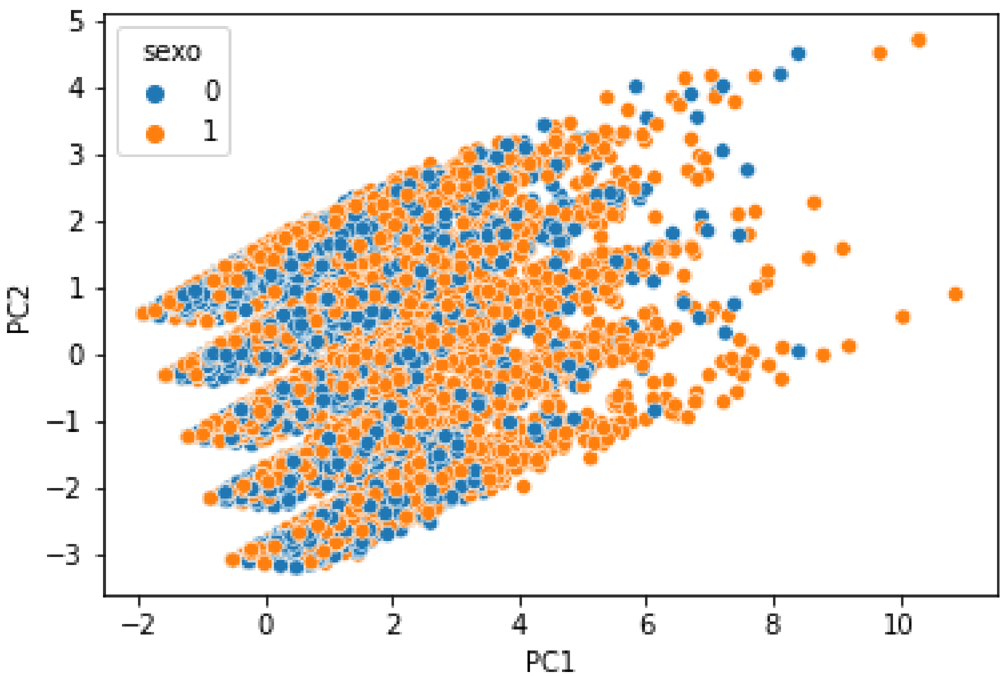


5 3

[35]:
```
pca_df['sexo'] = 0
pca_df['sexo'] = np.where(Xr["sexo"] > 0, 1, pca_df['sexo'])

sns.scatterplot('PC1', 'PC2', data=pca_df, hue='sexo')
```

```
C:\Users\Hpp\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

[35]: <AxesSubplot:xlabel='PC1', ylabel='PC2'>

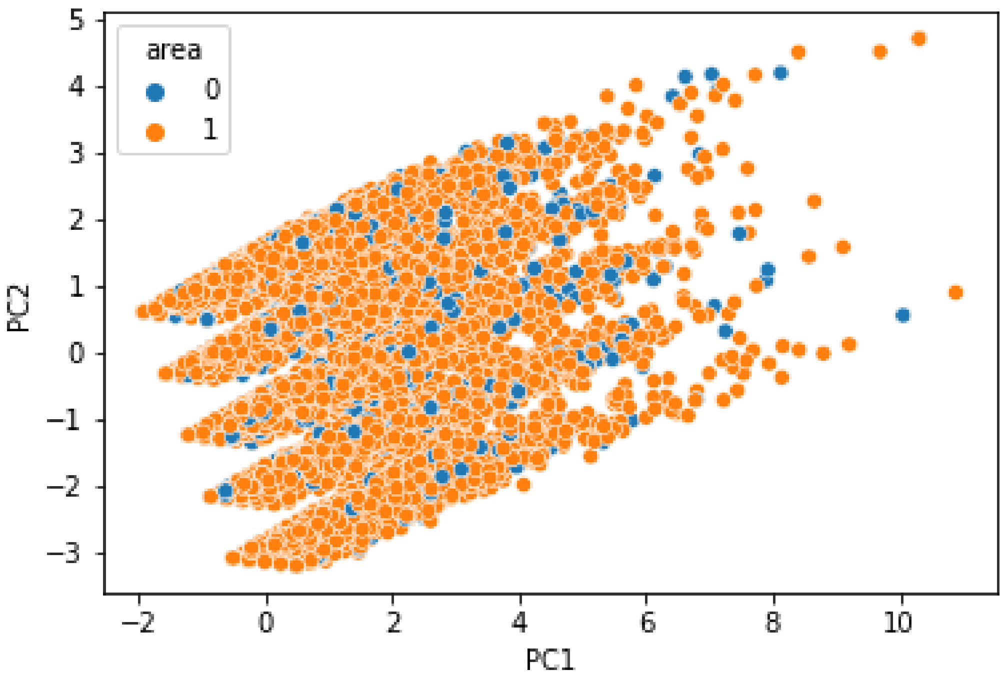


[36]:
```
pca_df['area'] = 0
pca_df['area'] = np.where(Xr["area"] > 0, 1, pca_df['area'])

sns.scatterplot('PC1', 'PC2', data=pca_df, hue='area')
```

```
C:\Users\Hpp\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
```

```
FutureWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

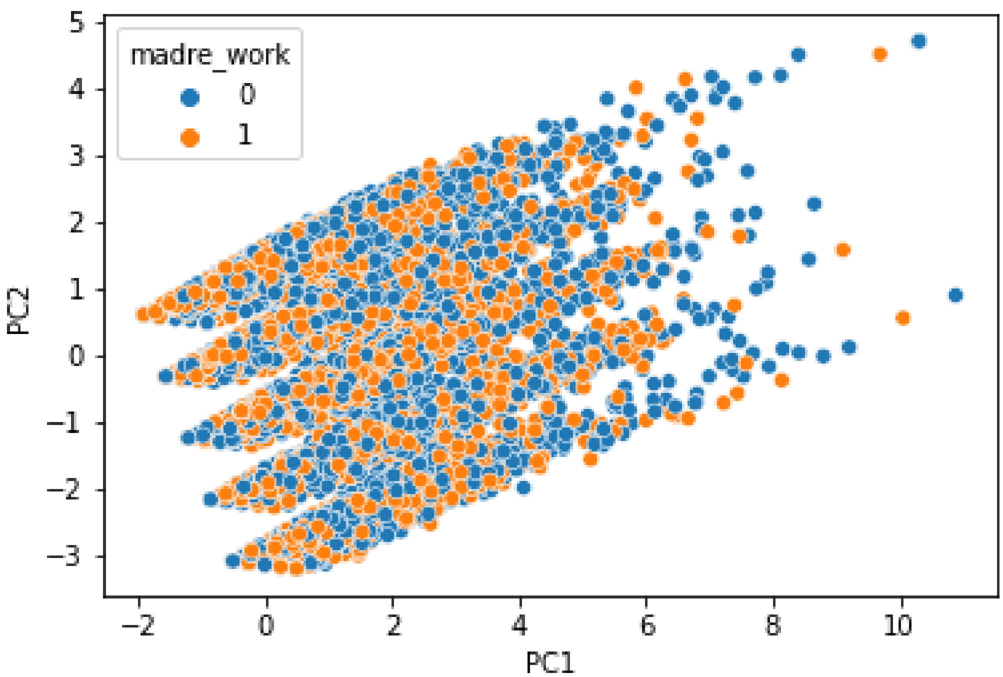
[36]: <AxesSubplot:xlabel='PC1', ylabel='PC2'>



[37]:
```
pca_df["madre_work"] = 0
pca_df["madre_work"] = np.where(Xr["madre_work"] > 0, 1, pca_df["madre_work"])

sns.scatterplot('PC1', 'PC2', data=pca_df, hue="madre_work")
```

```
C:\Users\Hpp\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

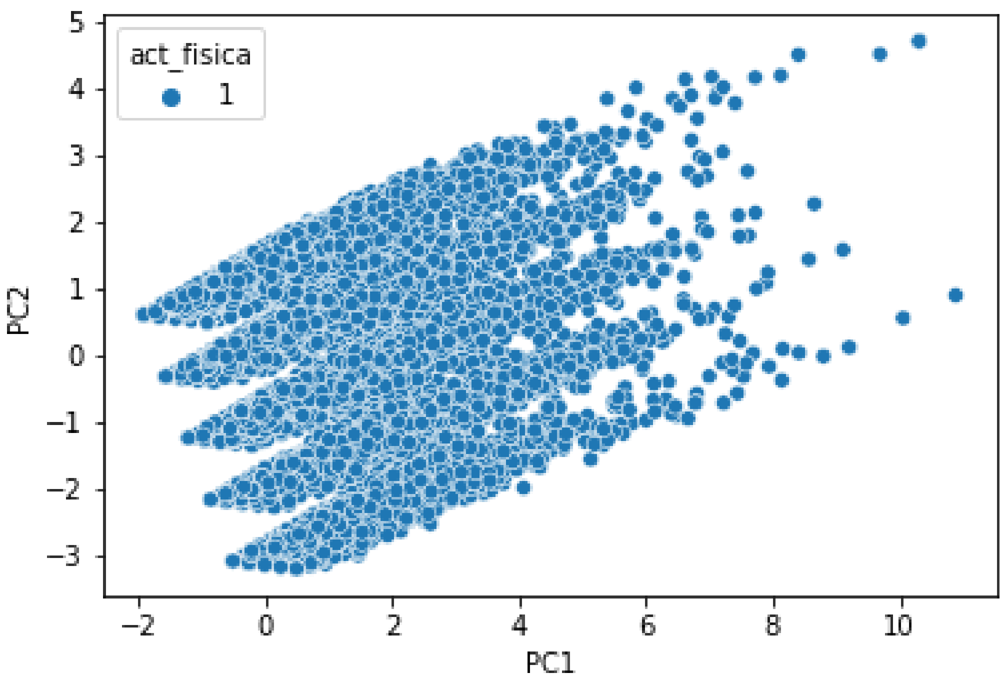
[37]: <AxesSubplot:xlabel='PC1', ylabel='PC2'>



[38]:
```
pca_df["act_fisica"] = 0
pca_df["act_fisica"] = np.where(Xr["act_fisica"] > 0, 1, pca_df["act_fisica"])

sns.scatterplot('PC1', 'PC2', data=pca_df, hue="act_fisica")
```

```
C:\Users\Hpp\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

[38]: <AxesSubplot:xlabel='PC1', ylabel='PC2'>



se puede observar que no existen diferencias significativas entre grupos , ya que no se observa una clara separación entre grupos con respecto a ambos ejes del gráfico

6 4

[ ]:
```
## Ser egoista modificamos sus valores
var_sk["sk7"].replace(4,2,inplace=True)
var_sk["sk7"].replace(5,1,inplace=True)
var_sk["sk7"].replace(2,4,inplace=True)
var_sk["sk7"].replace(1,5,inplace=True)
```

[40]:
```
fa = FactorAnalyzer(rotation='promax')
fa.fit(vector_sks)
```

[40]:
```
FactorAnalyzer(rotation_kwargs={})
```

[41]:
```
fa.loadings_
```

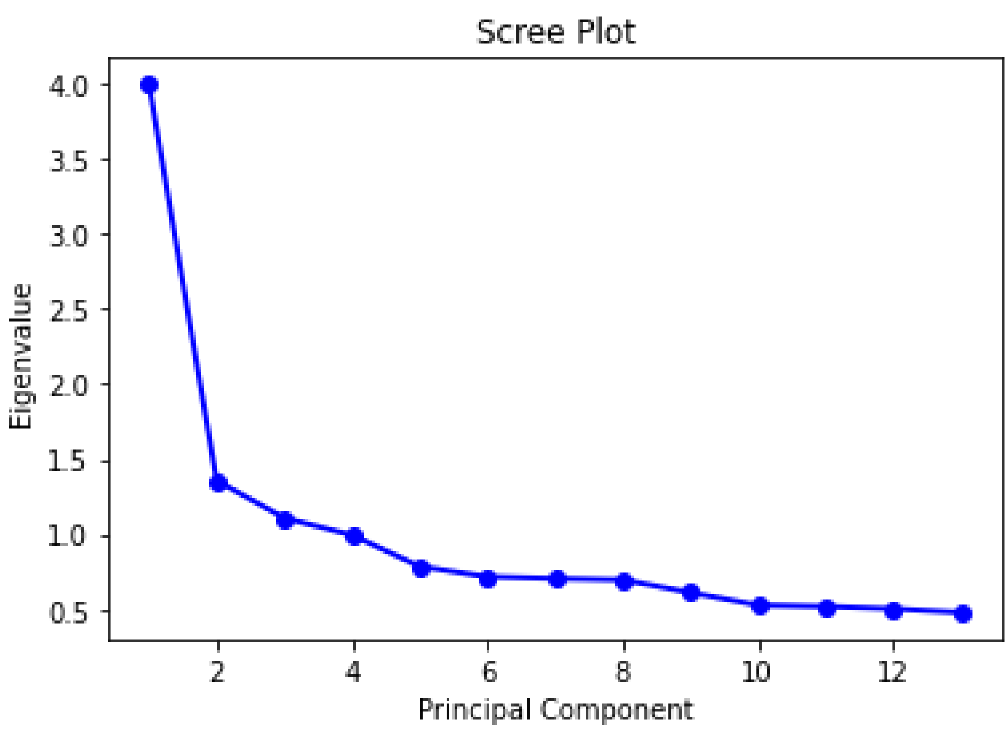
[41]:
```
array([[ 8.99735076e-03,  6.04089504e-01, -2.76161552e-02],
       [-3.08973511e-02,  4.81834611e-01,  2.44925078e-01],
       [ 3.18443234e-02,  6.38488215e-01, -4.60469009e-02],
       [-1.51671053e-04,  7.38733090e-01, -2.95482701e-02],
       [-1.42106910e-01, -1.64061245e-02,  8.46895012e-01],
       [-2.70462553e-04,  4.13009915e-02,  5.22560162e-01],
```

```
        [ 1.59537016e-02,  3.14375943e-02,  1.51335054e-01],
        [ 1.47858798e-01, -1.09890859e-01,  5.16256139e-01],
        [ 4.79056757e-01,  9.20273982e-02,  3.93230433e-02],
        [ 6.13861842e-01, -3.81052232e-02, -2.07578238e-02],
        [ 6.97308041e-01,  3.09136373e-02, -7.26688327e-04],
        [ 5.69219552e-01, -2.81948703e-02, -1.42155433e-03],
        [ 5.26432002e-01,  2.16588378e-02, -1.00089677e-02]])
```

[42]:
```
fa.get_eigenvalues()
```

[42]:
```
(array([3.99403324, 1.35709614, 1.10826633, 0.99384722, 0.78610007,
        0.71734716, 0.70564612, 0.69689018, 0.61153169, 0.52774476,
        0.51879723, 0.50343626, 0.47926359]),
 array([ 3.39429304,  0.75978216,  0.58015174,  0.2047792 ,  0.08742927,
         0.06254669,  0.03313104,  0.02348758, -0.02586072, -0.07677543,
        -0.09370486, -0.109146  , -0.17884126]))
```

[44]:
```
values = np.arange(1,14)
eigenvalues = pd.DataFrame(data=fa.get_eigenvalues())
plt.plot(values, eigenvalues.loc[0], 'o-', linewidth=2, color='blue')
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Eigenvalue')
plt.show()
```



[45]:
```
fa.get_factor_variance()
```

[45]:
```
(array([1.73806267, 1.57766252, 1.34554726]),
 array([0.13369713, 0.12135866, 0.10350364]),
 array([0.13369713, 0.25505578, 0.35855942]))
```

[48]:
```
print(semopy.efa.explore_cfa_model(vector_sks, pval=0.05))
```

```
eta1 =~ sk11 + sk9 + sk10 + sk12
eta2 =~ sk7 + sk6
eta3 =~ sk4 + sk2 + sk5 + sk11 + sk3 + sk9 + sk1 + sk6 + sk8 + sk12
eta4 =~ sk11 + sk12 + sk13
```

[51]:
```
efa_vectors = pd.DataFrame(data = fa.loadings_,
 ␣
 ↪index=["sk1","sk2","sk3","sk4","sk5","sk6","sk7","sk8","sk9","sk10","sk11","sk12","sk13"])
efa_vectors
```

[51]:

	0	1	2
sk1	0.008997	0.604090	-0.027616
sk2	-0.030897	0.481835	0.244925
sk3	0.031844	0.638488	-0.046047
sk4	-0.000152	0.738733	-0.029548
sk5	-0.142107	-0.016406	0.846895
sk6	-0.000270	0.041301	0.522560
sk7	0.015954	0.031438	0.151335
sk8	0.147859	-0.109891	0.516256
sk9	0.479057	0.092027	0.039323
sk10	0.613862	-0.038105	-0.020758
sk11	0.697308	0.030914	-0.000727
sk12	0.569220	-0.028195	-0.001422
sk13	0.526432	0.021659	-0.010009

- En el grupo 0 quedará sk9,sk10,sk11,sk12,sk13 (intelectuales-curiosos);
- En el grupo 1 quedará sk1,sk2,sk3,sk4 (cariñosos);
- En el grupo 2 quedará sk5,sk6,sk7,sk8(sociables)

7 5

[52]:
```
Xf=vector_sks

mod = """
# measurement model
```

```
eta1 =~ sk9 + sk10 + sk11 + sk12 + sk13
eta2 =~ sk1 + sk2 + sk3 + sk4
eta3 =~ sk5 + sk6 + sk7 + sk8
    """

model = semopy.Model(mod)
out=model.fit(Xf)
print(out)
```

```
Name of objective: MLW
Optimization method: SLSQP
Optimization successful.
Optimization terminated successfully
Objective value: 0.164
Number of iterations: 40
Params: 1.393 1.256 1.144 1.351 1.924 1.625 1.781 1.042 0.572 1.143 0.478 0.239
1.429 0.440 0.203 0.156 0.277 0.594 0.700 0.090 0.201 0.160 0.360 0.141 0.087
0.048 0.157 0.057 0.047
```

[53]:
```
model.inspect(mode='list', what="names", std_est=True)
```

[53]:

	lval	op	rval	Estimate	Est. Std	Std. Err	z-value	p-value
0	sk9	~	eta1	1.000000	0.580567	-	-	-
1	sk10	~	eta1	1.393283	0.561740	0.016007	87.039845	0.0
2	sk11	~	eta1	1.256019	0.722753	0.012557	100.023741	0.0
3	sk12	~	eta1	1.144320	0.543799	0.013443	85.121476	0.0
4	sk13	~	eta1	1.350601	0.518536	0.016411	82.29952	0.0
5	sk1	~	eta2	1.000000	0.586883	-	-	-
6	sk2	~	eta2	1.923701	0.650616	0.019852	96.902529	0.0
7	sk3	~	eta2	1.625467	0.619708	0.01727	94.118211	0.0
8	sk4	~	eta2	1.780563	0.695271	0.017746	100.334697	0.0
9	sk5	~	eta3	1.000000	0.708895	-	-	-
10	sk6	~	eta3	1.041920	0.566983	0.0118	88.300274	0.0
11	sk7	~	eta3	0.571564	0.186279	0.017336	32.969296	0.0
12	sk8	~	eta3	1.142588	0.548128	0.013232	86.352139	0.0
13	eta1	~~	eta1	0.141058	1.000000	0.00241	58.538392	0.0
14	eta1	~~	eta3	0.086894	0.583468	0.001321	65.772745	0.0
15	eta1	~~	eta2	0.048393	0.592172	0.000754	64.196223	0.0
16	eta3	~~	eta3	0.157234	1.000000	0.002309	68.099692	0.0
17	eta3	~~	eta2	0.056983	0.660446	0.000804	70.900865	0.0
18	eta2	~~	eta2	0.047344	1.000000	0.000794	59.602994	0.0
19	sk8	~~	sk8	0.477951	0.699556	0.003866	123.623766	0.0
20	sk2	~~	sk2	0.238696	0.576699	0.002049	116.507167	0.0
21	sk7	~~	sk7	1.428924	0.965300	0.009713	147.114692	0.0
22	sk12	~~	sk12	0.439910	0.704283	0.003382	130.062828	0.0
23	sk11	~~	sk11	0.203470	0.477629	0.002053	99.087724	0.0
24	sk5	~~	sk5	0.155650	0.497468	0.001763	88.276716	0.0

```
25   sk9  ~~   sk9  0.277440  0.662942  0.002203  125.927537     0.0
26  sk10  ~~  sk10  0.593947  0.684449  0.004635  128.145625     0.0
27  sk13  ~~  sk13  0.699653  0.731120  0.005281  132.479658     0.0
28   sk1  ~~   sk1  0.090112  0.655568  0.000715  125.973925     0.0
29   sk3  ~~   sk3  0.200634  0.615962  0.001651   121.53224     0.0
30   sk4  ~~   sk4  0.160409  0.516598  0.001493  107.443359     0.0
31   sk6  ~~   sk6  0.360284  0.678531  0.002981  120.845663     0.0
```

[54]:
```
semopy.calc_stats(model)
```

[54]:
```
       DoF  DoF Baseline         chi2  chi2 p-value  chi2 Baseline       CFI  \
Value   62            78  7300.357081           0.0  120370.676623  0.939827

            GFI    AGFI       NFI       TLI    RMSEA        AIC         BIC  \
Value  0.939351  0.9237  0.939351  0.924299  0.05122  57.671909  310.067302

         LogLik
Value  0.164046
```

[ ]: