

Tarea 4 SEM Javiera San Martín

June 14, 2023

Section 5: Structural Equation Modelling

0.1 Housekeeping and Data

[1]: pip install semopy

```
Requirement already satisfied: semopy in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (2.3.9)
Requirement already satisfied: sklearn in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from semopy) (0.0)
Requirement already satisfied: pandas in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from semopy)
(1.2.4)
Requirement already satisfied: scipy in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from semopy)
(1.6.2)
Requirement already satisfied: statsmodels in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from semopy)
(0.12.2)
Requirement already satisfied: sympy in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from semopy) (1.8)
Requirement already satisfied: numpy in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from semopy)
(1.20.1)
Requirement already satisfied: python-dateutil>=2.7.3 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
pandas->semopy) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
pandas->semopy) (2021.1)
Requirement already satisfied: six>=1.5 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from python-
dateutil>=2.7.3->pandas->semopy) (1.15.0)
Requirement already satisfied: scikit-learn in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
sklearn->semopy) (1.2.2)
Requirement already satisfied: joblib>=1.1.1 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from scikit-
```

```
learn->sklearn->semopy) (1.2.0)
Requirement already satisfied: threadpoolct1>=2.0.0 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from scikit-learn->sklearn->semopy) (2.1.0)
Requirement already satisfied: patsy>=0.5 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from statsmodels->semopy) (0.5.1)
Requirement already satisfied: mpmath>=0.19 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from sympy->semopy) (1.2.1)
Note: you may need to restart the kernel to use updated packages.
```

[2]: pip install factor_analyzer

```
Requirement already satisfied: factor_analyzer in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (0.4.1)
Requirement already satisfied: scikit-learn in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
factor_analyzer) (1.2.2)
Requirement already satisfied: pandas in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
factor_analyzer) (1.2.4)
Requirement already satisfied: scipy in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
factor analyzer) (1.6.2)
Requirement already satisfied: pre-commit in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
factor_analyzer) (3.3.2)
Requirement already satisfied: numpy in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
factor_analyzer) (1.20.1)
Requirement already satisfied: python-dateutil>=2.7.3 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
pandas->factor_analyzer) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
pandas->factor_analyzer) (2021.1)
Requirement already satisfied: six>=1.5 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from python-
dateutil>=2.7.3->pandas->factor_analyzer) (1.15.0)
Requirement already satisfied: nodeenv>=0.11.1 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from pre-
commit->factor_analyzer) (1.8.0)
Requirement already satisfied: virtualenv>=20.10.0 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from pre-
commit->factor_analyzer) (20.23.0)
Requirement already satisfied: identify>=1.0.0 in
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from pre-
```

```
commit->factor_analyzer) (2.5.24)
    Requirement already satisfied: pyyaml>=5.1 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from pre-
    commit->factor_analyzer) (5.4.1)
    Requirement already satisfied: cfgv>=2.0.0 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from pre-
    commit->factor analyzer) (3.3.1)
    Requirement already satisfied: setuptools in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
    nodeenv>=0.11.1->pre-commit->factor_analyzer) (52.0.0.post20210125)
    Requirement already satisfied: filelock<4,>=3.11 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
    virtualenv>=20.10.0->pre-commit->factor_analyzer) (3.12.2)
    Requirement already satisfied: platformdirs<4,>=3.2 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
    virtualenv>=20.10.0->pre-commit->factor_analyzer) (3.5.3)
    Requirement already satisfied: distlib<1,>=0.3.6 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
    virtualenv>=20.10.0->pre-commit->factor_analyzer) (0.3.6)
    Requirement already satisfied: joblib>=1.1.1 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from scikit-
    learn->factor analyzer) (1.2.0)
    Requirement already satisfied: threadpoolctl>=2.0.0 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from scikit-
    learn->factor_analyzer) (2.1.0)
    Note: you may need to restart the kernel to use updated packages.
[3]: pip install stepmix
    Requirement already satisfied: stepmix in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (1.1.1)
    Requirement already satisfied: pandas in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from stepmix)
    (1.2.4)
    Requirement already satisfied: numpy in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from stepmix)
    Requirement already satisfied: scikit-learn>=1.0.0 in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from stepmix)
    Requirement already satisfied: scipy in
    /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from stepmix)
```

/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from stepmix)

/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from stepmix)

Requirement already satisfied: tqdm in

Requirement already satisfied: matplotlib in

```
(3.3.4)
     Requirement already satisfied: threadpoolctl>=2.0.0 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from scikit-
     learn>=1.0.0->stepmix) (2.1.0)
     Requirement already satisfied: joblib>=1.1.1 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from scikit-
     learn>=1.0.0->stepmix) (1.2.0)
     Requirement already satisfied: pillow>=6.2.0 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     matplotlib->stepmix) (8.2.0)
     Requirement already satisfied: cycler>=0.10 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     matplotlib->stepmix) (0.10.0)
     Requirement already satisfied: python-dateutil>=2.1 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     matplotlib->stepmix) (2.8.1)
     Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     matplotlib->stepmix) (2.4.7)
     Requirement already satisfied: kiwisolver>=1.0.1 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     matplotlib->stepmix) (1.3.1)
     Requirement already satisfied: six in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     cycler>=0.10->matplotlib->stepmix) (1.15.0)
     Requirement already satisfied: pytz>=2017.3 in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (from
     pandas->stepmix) (2021.1)
     Note: you may need to restart the kernel to use updated packages.
 [4]: pip install graphviz
     Requirement already satisfied: graphviz in
     /Users/macbookair/opt/anaconda3/lib/python3.8/site-packages (0.20.1)
     Note: you may need to restart the kernel to use updated packages.
[68]: 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
from IPython.display import Image

%matplotlib inline
```

0.2 Pregunta 1

Cargue la base de datos y realice los ajustes necesarios para su uso (missing values, recodificar variables, etcetera). Identifique los tipos de datos que se encuentran en la base, realice estadisticas descriptivas sobre las variables importantes (Hint: Revisar la distribuciones, datos faltantes, outliers, etc.) y limpie las variables cuando sea necesario.

• El análisis de los datos se realizó en el anexo 1.

Descripciones:

- AcceptedCmp1 = 1 si el cliente aceptó la oferta en la 1ra campaña, 0 de lo contrario
- AcceptedCmp2 = 1 si el cliente aceptó la oferta en la 2da campaña, 0 de lo contrario
- AcceptedCmp3 = 1 si el cliente aceptó la oferta en la 3ra campaña, 0 de lo contrario
- AcceptedCmp4 = 1 si el cliente aceptó la oferta en la 4ta campaña, 0 de lo contrario
- AcceptedCmp5 = 1 si el cliente aceptó la oferta en la 5ta campaña, 0 de lo contrario
- Response (target) = 1 si el cliente aceptó la oferta en la última campaña, 0 de lo contrario
- Complain = 1 si el cliente se quejó en los últimos 2 años
- DtCustomer = fecha de inscripción del cliente en la empresa
- Education = nivel de educación del cliente
- Marital = estado civil
- Kidhome = número de niños pequeños en el hogar
- Teenhome = número de adolescentes en el hogar
- Income = ingresos familiares anuales
- MntFishProducts = cantidad gastada en pescados (productos del mar) en los últimos 2 años
- MntMeatProducts = cantidad gastada en carne en los últimos 2 años
- MntFruits = cantidad gastada en frutas en los últimos 2 años
- MntSweetProducts = cantidad gastada en productos dulces en los últimos 2 años
- MntWines = cantidad gastada en vino en los últimos 2 años
- MntGoldProds = cantidad gastada en productos de "lujo" en los últimos 2 años
- NumDealsPurchases = número de compras realizadas con descuento
- NumCatalogPurchases = número de compras realizadas utilizando el catálogo
- NumStorePurchases = número de compras realizadas directamente en las tiendas
- NumWebPurchases = número de compras realizadas a través del sitio web de la empresa
- NumWebVisitsMonth = número de visitas al sitio web de la empresa en el último mes
- Recency = número de días desde la última compra

```
[69]: df_food=pd.read_csv('../data/ifood_df.csv')
#data description
df_food.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2205 entries, 0 to 2204
Data columns (total 39 columns):

#	Column	Non-Null Count	Dtype	
0	Income	2205 non-null	float64	
1	Kidhome	2205 non-null	int64	
2	Teenhome	2205 non-null	int64	
3	Recency	2205 non-null	int64	
4	MntWines	2205 non-null	int64	
5	MntFruits	2205 non-null	int64	
6	MntMeatProducts	2205 non-null	int64	
7	${ t MntFishProducts}$	2205 non-null	int64	
8	MntSweetProducts	2205 non-null	int64	
9	MntGoldProds	2205 non-null	int64	
10	NumDealsPurchases	2205 non-null	int64	
11	NumWebPurchases	2205 non-null	int64	
12	${\tt NumCatalogPurchases}$	2205 non-null	int64	
13	NumStorePurchases	2205 non-null	int64	
14	NumWebVisitsMonth	2205 non-null	int64	
15	AcceptedCmp3	2205 non-null	int64	
16	AcceptedCmp4	2205 non-null	int64	
17	AcceptedCmp5	2205 non-null	int64	
18	AcceptedCmp1	2205 non-null	int64	
19	AcceptedCmp2	2205 non-null	int64	
20	Complain	2205 non-null	int64	
21	Z_CostContact	2205 non-null	int64	
22	Z_Revenue	2205 non-null	int64	
23	Response	2205 non-null	int64	
24	Age	2205 non-null	int64	
25	Customer_Days	2205 non-null	int64	
26	${ t marital_Divorced}$	2205 non-null	int64	
27	${ t marital_Married}$	2205 non-null	int64	
28	marital_Single	2205 non-null	int64	
29	marital_Together	2205 non-null	int64	
30	${ t marital_Widow}$	2205 non-null	int64	
31	education_2n Cycle	2205 non-null	int64	
32	education_Basic	2205 non-null	int64	
33	${\tt education_Graduation}$	2205 non-null	int64	
34	education_Master	2205 non-null	int64	
35	education_PhD	2205 non-null	int64	
36	MntTotal	2205 non-null	int64	
37	MntRegularProds	2205 non-null	int64	
38	AcceptedCmpOverall	2205 non-null	int64	
dtypes: float64(1), int64(38)				

dtypes: float64(1), int64(38)

memory usage: 672.0 KB

[70]: df_food.describe()

[70]:		Income	Kidhome	Teenhom	e Recency	y MntWines	\
	count	2205.000000	2205.000000	2205.00000			
	mean	51622.094785	0.442177	0.50657	6 49.009070	306.164626	
	std	20713.063826	0.537132	0.54438	0 28.93211	1 337.493839	
	min	1730.000000	0.000000	0.00000	0.00000	0.000000	
	25%	35196.000000	0.000000	0.00000	0 24.00000	24.000000	
	50%	51287.000000	0.000000	0.00000	0 49.00000	178.000000	
	75%	68281.000000	1.000000	1.00000	0 74.00000	507.000000	
	max	113734.000000	2.000000	2.00000	0 99.00000	1493.000000	
		MntFruits	MntMeatProduc [.]	ts MntFishP	roducts Mn+S	weetProducts \	\
	count	2205.000000	2205.0000		.000000	2205.000000	\
		26.403175	165.3120		.756463	27.128345	
	mean	39.784484	217.7845		.824635	41.130468	
	std						
	min	0.000000 2.000000	0.0000 16.0000		.000000	0.000000 1.000000	
	25%						
	50%	8.000000	68.0000		.000000	8.000000	
	75%	33.000000	232.0000		.000000	34.000000	
	max	199.000000	1725.0000	00 259	.000000	262.000000	
		${\tt MntGoldProds}$	marital_T	ogether mar	ital_Widow e	ducation_2n Cyc	cle \
	count	2205.000000	2205	.000000 2	205.000000	2205.0000	000
	mean	44.057143	0	. 257596	0.034467	0.0897	796
	std	51.736211	0	.437410	0.182467	0.2859	954
	min	0.000000	0	.000000	0.000000	0.0000	000
	25%	9.000000	0	.000000	0.000000	0.0000	000
	50%	25.000000	0	.000000	0.000000	0.0000	000
	75%	56.000000	1	.000000	0.000000	0.0000	000
	max	321.000000	1	.000000	1.000000	1.0000	000
		education_Bas	ic education	_Graduation	education_Mag	ster education	n PhD \
	count	2205.0000		2205.000000	2205.000		
	mean	0.0244	90	0.504762	0.16	5079 0.23	15873
	std	0.1545	99	0.500091	0.37	1336 0.43	11520
	min	0.0000	00	0.000000	0.000		00000
	25%	0.0000		0.000000	0.000		00000
	50%	0.0000		1.000000	0.000		00000
	75%	0.0000		1.000000	0.000		00000
	max	1.0000		1.000000	1.000		00000
		${\tt MntTotal}$	${ t MntRegular Pro}$	-	${\tt CmpOverall}$		
	count	2205.000000	2205.0000	00	2205.00000		
	mean	562.764626	518.7074	83	0.29932		
	std	575.936911	553.8472	48	0.68044		
	min	4.000000	-283.0000	00	0.00000		

25%	56.000000	42.000000	0.00000
50%	343.000000	288.000000	0.00000
75%	964.000000	884.000000	0.00000
max	2491.000000	2458.000000	4.00000

[8 rows x 39 columns]

Correr anexo 1 luego el resto del código.

```
[83]: df_food2= df_food[['MntWines',"MntFruits", "MntMeatProducts", "
       →"MntFishProducts", "MntSweetProducts", "MntGoldProds", "NumDealsPurchases", 
       →"NumWebPurchases", "NumCatalogPurchases", 
       →"NumStorePurchases","NumWebVisitsMonth"]]
      df_food.describe()
[83]:
                     Income
                                 Kidhome
                                              Teenhome
                                                             Recency
                                                                          MntWines
                                                                                    \
               2181.000000
                             2181.000000
                                           2181.000000
                                                         2181.000000
                                                                       2181.000000
      count
      mean
              51479.366804
                                 0.446584
                                              0.512150
                                                           49.025676
                                                                        303.548372
              20552.087114
      std
                                 0.538017
                                              0.544753
                                                           28.987854
                                                                        334.635002
               1730.000000
                                 0.000000
                                              0.00000
                                                            0.000000
                                                                          0.00000
      min
      25%
              35196.000000
                                 0.000000
                                              0.000000
                                                           24.000000
                                                                         24.000000
      50%
              51124.000000
                                 0.00000
                                              0.000000
                                                           49.000000
                                                                        174.000000
      75%
              67893.000000
                                              1.000000
                                                           74.000000
                                                                        505.000000
                                 1.000000
                                              2.000000
      max
             113734.000000
                                 2.000000
                                                           99.000000
                                                                       1493.000000
                                             MntFishProducts
               MntFruits
                           MntMeatProducts
                                                               MntSweetProducts
             2181.000000
                               2181.000000
                                                  2181.000000
                                                                     2181.000000
      count
               26.146263
                                 161.785420
      mean
                                                    37.286566
                                                                       26.814764
      std
               39.519130
                                 212.083811
                                                    54.409878
                                                                       40.893861
      min
                0.000000
                                   1.000000
                                                                        0.00000
                                                     0.000000
      25%
                 2.000000
                                 16.000000
                                                     3.000000
                                                                        1.000000
      50%
                8.000000
                                 67.000000
                                                    12.000000
                                                                        8.000000
      75%
               33.000000
                                 224.000000
                                                                       33.000000
                                                    49.000000
              199.000000
                                 984.000000
                                                   259.000000
                                                                      262.000000
      max
             MntGoldProds
                               marital_Together
                                                  marital_Widow
                                                                   education_2n Cycle
      count
              2181.000000
                                     2181.000000
                                                     2181.000000
                                                                          2181.000000
                                        0.259055
                                                        0.034846
                                                                             0.088950
                 43.841357
      mean
      std
                 51.544891
                                        0.438217
                                                        0.183433
                                                                             0.284737
                 0.000000
                                        0.00000
                                                        0.000000
                                                                             0.000000
      min
      25%
                 9.000000
                                                                             0.00000
                                        0.000000
                                                        0.000000
      50%
                 24.000000
                                        0.000000
                                                        0.000000
                                                                             0.000000
      75%
                 56.000000
                                        1.000000
                                                        0.000000
                                                                             0.000000
      max
               321.000000
                                        1.000000
                                                        1.000000
                                                                             1.000000
             education_Basic
                                                                          education_PhD
                               education_Graduation
                                                       education_Master
                 2181.000000
                                         2181.000000
                                                            2181.000000
                                                                            2181.000000
      count
```

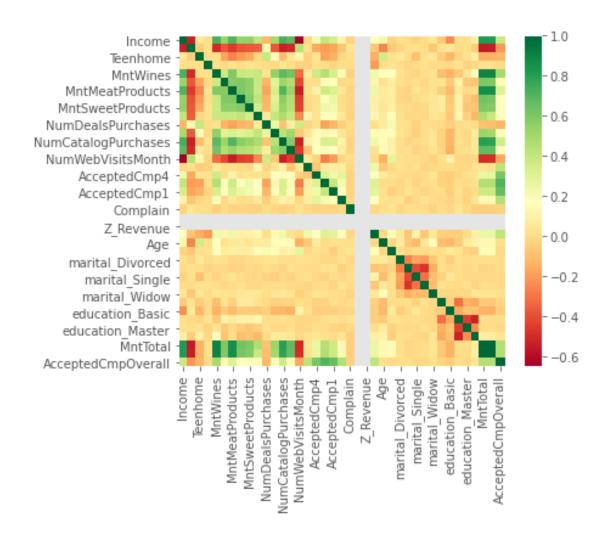
mean	0.024301	0.503439	0.165979	0.217331
std	0.154017	0.500103	0.372147	0.412525
min	0.00000	0.000000	0.000000	0.000000
25%	0.00000	0.000000	0.000000	0.000000
50%	0.00000	1.000000	0.000000	0.000000
75%	0.00000	1.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

	${ t MntTotal}$	${ t MntRegular Prods}$	AcceptedCmpOverall
count	2181.000000	2181.000000	2181.000000
mean	555.581385	511.740028	0.292526
std	568.109267	545.940078	0.668892
min	4.000000	-283.000000	0.000000
25%	55.000000	42.000000	0.000000
50%	341.000000	283.000000	0.000000
75%	956.000000	873.000000	0.000000
max	2262.000000	2145.000000	4.000000

[8 rows x 39 columns]

```
[86]: fig, ax = plt.subplots(1,1, figsize = (6,5))
sns.heatmap(df_food.corr(), cmap='RdYlGn')
```

[86]: <AxesSubplot:>



0.3 PCA

0.4 Pregunta 2

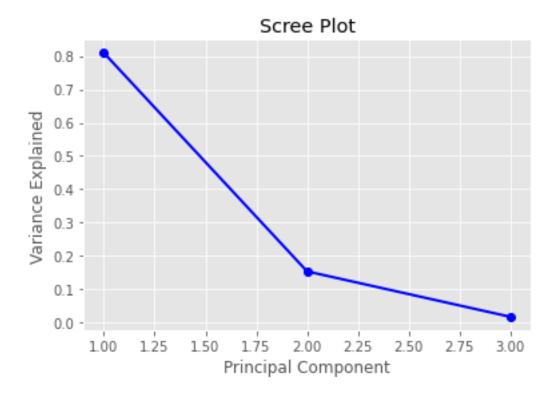
Realice un PCA usando las variables de numero de compras y cantidad gastada en los diversos items. En particular, identifique los valores propios y determine el numero optimo de componentes. Luego estime y grafique la distribución de los componentes. Ademas discuta la importancia relativa de las variables sobre cada uno de los componentes estimados. Que se puede concluir de este analisis?

```
[87]: pca = PCA(n_components=11)
pca_food = pca.fit_transform(df_food2)
print(pca.explained_variance_ratio_)
```

```
[8.09613601e-01 1.53633686e-01 1.72435003e-02 9.80944075e-03 5.41209224e-03 4.16871385e-03 4.04401296e-05 3.49445475e-05 1.82800045e-05 1.47332062e-05 1.05674635e-05]
```



[0.8096136 0.15363369 0.0172435]



Se realizó un un scree plot con el total de variables utilizadas. En este se observa que hay 3 variables significativas que explican gran parte de la varianza. Se realiza un nuevo PCA con las 3 variables, se grafica y se obtienen los valores propios de 0.8096136, 0.15363369 y 0.0172435

```
[93]: pca_vectors = pd.DataFrame(data = pca.components_)
      pca_vectors.head()
[93]:
                          1
                                              3
                                                         4
                                                                   5
                                                                                  \
         0.891857
                   0.051131
                              0.435924
                                        0.073443
                                                  0.052437
                                                             0.060932 -0.000156
      1 -0.450746
                   0.093793
                              0.870967
                                        0.139092
                                                  0.091635
                                                             0.040584 -0.002899
      2 -0.028419
                   0.321124 -0.206453
                                        0.585234
                                                  0.322424
                                                             0.637666 0.001508
               7
                          8
                                    9
                                              10
                             0.005892 -0.002718
         0.004092
                   0.005627
      1 -0.001684
                   0.003838
                              0.001108 -0.005467
      2 0.010642
                   0.009924
                             0.011377 -0.005649
[94]: pca_df = pd.DataFrame(data=pca_features,columns=["PC1", "PC2", "PC3"])
      pca_df.describe().apply(lambda s: s.apply('{0:.3f}'.format))
[94]:
                  PC1
                             PC2
                                       PC3
             2181.000
                       2181.000
                                  2181.000
      count
      mean
                0.000
                          -0.000
                                     0.000
```

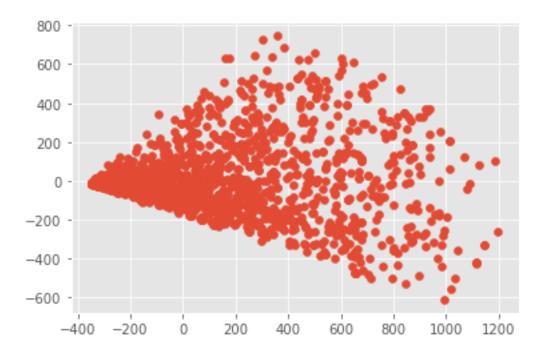
```
std
        366.431
                  159.623
                              53.477
       -348.152
                 -610.364
                           -192.779
min
25%
       -319.762
                  -50.157
                             -24.796
50%
       -141.615
                  -11.246
                             -14.260
75%
        240.733
                   19.298
                             15.020
       1197.561
                  745.618
                             261.020
max
```

```
[95]: pca_df.corr().apply(lambda s: s.apply('{0:.3f}'.format))
```

```
[95]:
               PC1
                       PC2
                                PC3
                    -0.000
      PC1
             1.000
                              0.000
      PC2
           -0.000
                     1.000
                             -0.000
      PC3
            0.000
                    -0.000
                              1.000
```

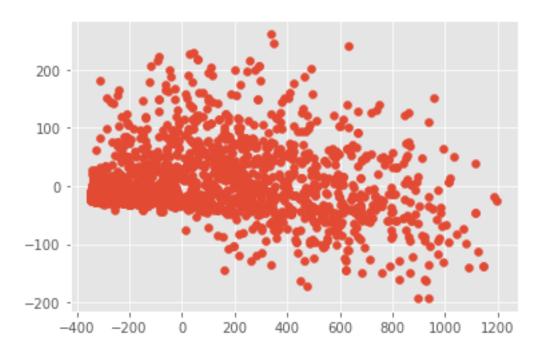
```
[97]: plt.scatter(pca_df["PC1"],pca_df['PC2'])
```

[97]: <matplotlib.collections.PathCollection at 0x7fb8ed56e7f0>



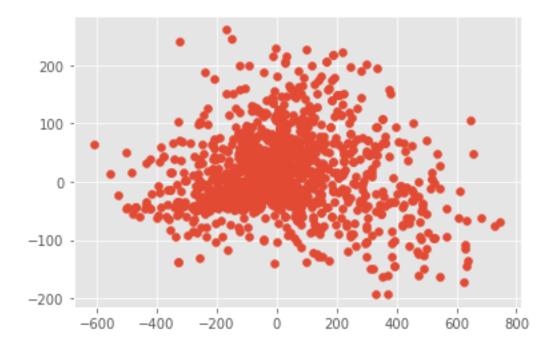
```
[98]: plt.scatter(pca_df["PC1"],pca_df["PC3"])
```

[98]: <matplotlib.collections.PathCollection at 0x7fb8ed2faa90>



[99]: plt.scatter(pca_df['PC2'],pca_df["PC3"])

[99]: <matplotlib.collections.PathCollection at 0x7fb907e11550>



Se observa en el gráfico PC1 vs PC2 cierta tendencia horizontal con pendiente negativa. En el

gráfico PC1 vs PC3 se observa una tendencia horizontal, mientras que en el gráfico PC2 vs PC3 se observa una dispersión de los datos por lo que no se puede realizar una conclución con certeza.

0.5 Pregunta 3

Con los resultados de la Pregunta 2, mantenga los primeros 3 componentes principales y repita el analisis. Graficamente y estadisticamente indique si existen diferencias o relaciones significativas entre los valores de los PCA y las siguientes variables: Income, Kidhome, Education y Recency. Que puede concluir de los resultados?

[9.99998009e-01 1.98925361e-06 8.08638668e-10]



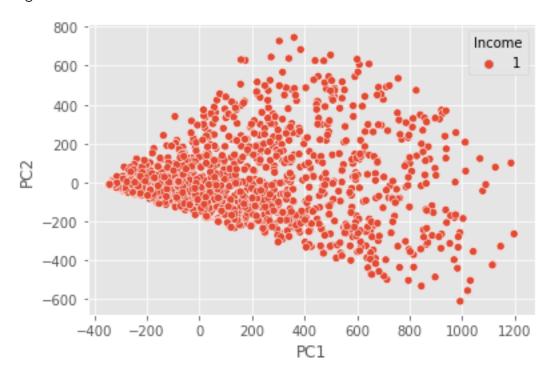
[120]: V1 = "Income";

pca_df[V1] = 0;

/Users/macbookair/opt/anaconda3/lib/python3.8/sitepackages/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

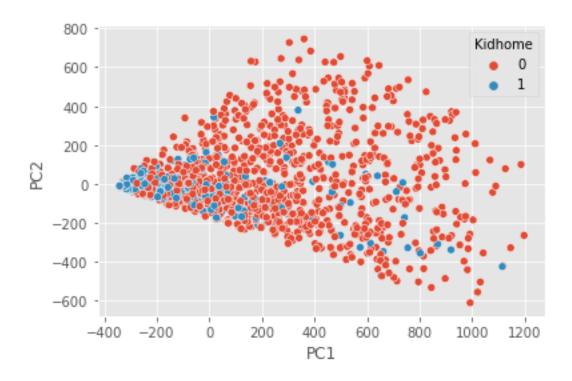
pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);

result in an error or misinterpretation.
warnings.warn(

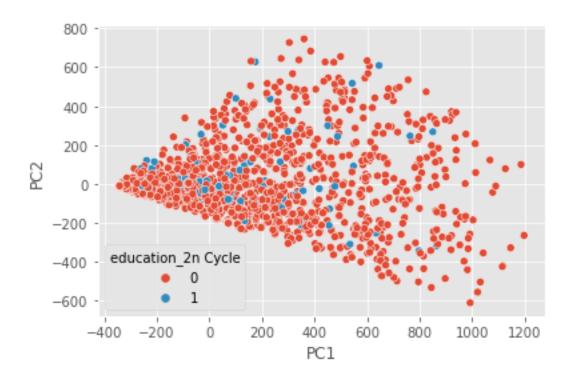


```
[121]: V1 = "Kidhome";
    pca_df[V1] = 0;
    pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
    sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```

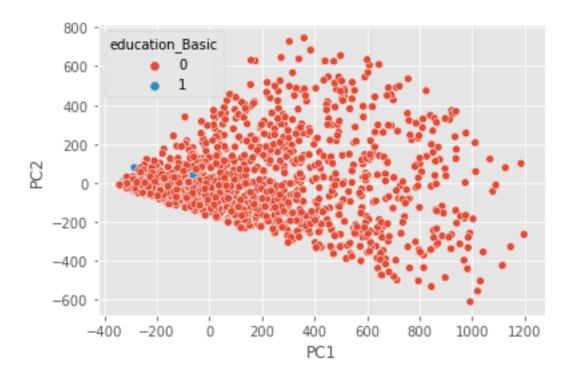
/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.



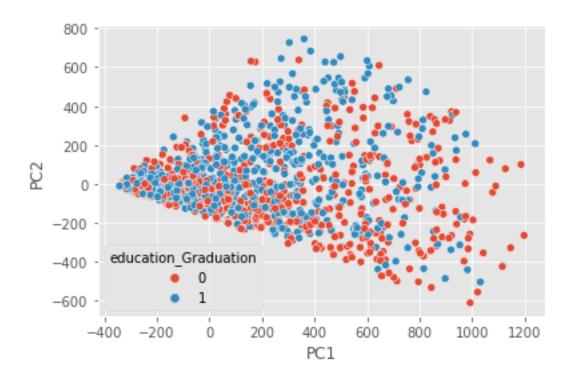
```
[122]: V1 = "education_2n Cycle";
    pca_df[V1] = 0;
    pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
    sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```



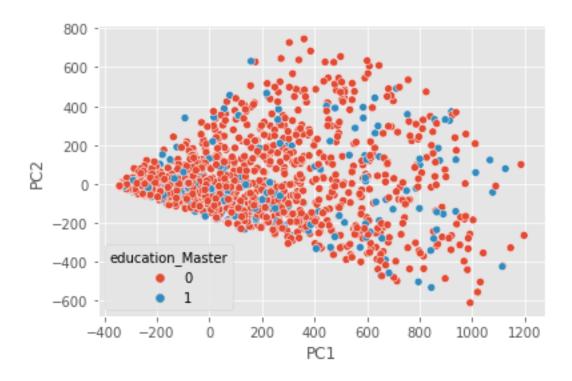
```
[123]: V1 = "education_Basic";
   pca_df[V1] = 0;
   pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
   sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```



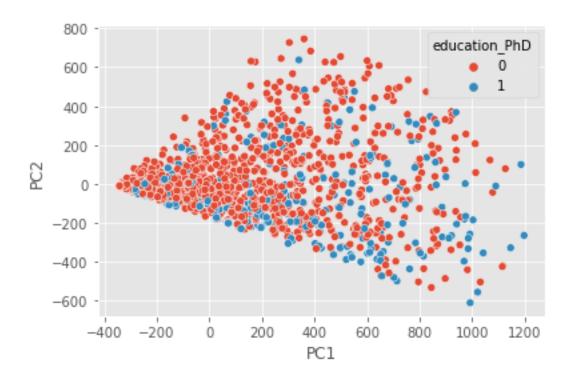
```
[124]: V1 ="education_Graduation";
  pca_df[V1] = 0;
  pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
  sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```



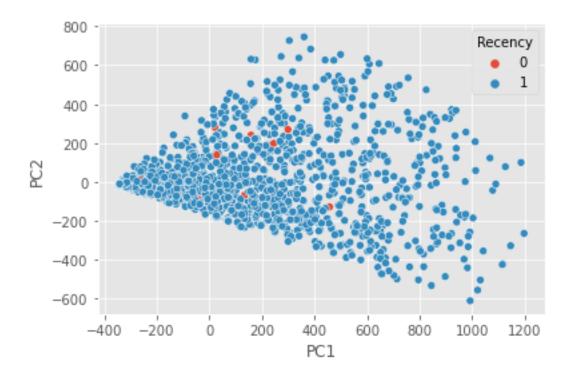
```
[125]: V1 = "education_Master";
   pca_df[V1] = 0;
   pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
   sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```



```
[126]: V1 = "education_PhD";
    pca_df[V1] = 0;
    pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
    sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```



```
[127]: V1 = "Recency";
    pca_df[V1] = 0;
    pca_df[V1] = np.where(df_food[V1] > 0, 1, pca_df[V1]);
    sns.scatterplot("PC1", "PC2", data=pca_df, hue=V1);
```



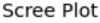
Para las variables Income, education_2n Cycle, education_Basic no se muestrna diferencias significativas o visbles, por Lo que no se puede asumir que alguno de los dos factores tengan mayor influencia. Para las variables Kidhome, education_Graduation, education_Master, education_PhD se observa una diferencia significativa en el eje horizontal por lo que se puede asumir que el factor PC2 tiene mayor relación.

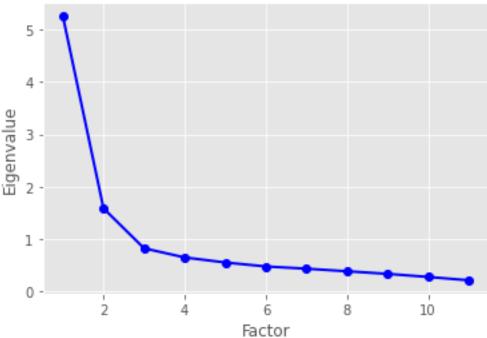
0.6 EFA

0.7 Pregunta 4

A partir del mismo set de variables de la pregunta 2 realice un EFA. En particular determine el numero optimo de factores y las variables que se asocian a cada factor. Tambien discuta si existen variables que no son informativas.

```
[-0.0941634, 0.84901382, -0.04932061],
             [-0.04215036, 0.76001832, -0.02803789],
              [ 0.20249502, 0.42644171, 0.16994652],
              [0.09657193, -0.02952742, 0.62094574],
             [0.54320024, 0.16808687, 0.46217645],
             [0.64679782, 0.20954901, -0.15335873],
              [0.64296387, 0.14461263, 0.04811019],
                        , -0.1899502 , 0.54607509]])
              [-0.29679
[130]: fa.get_eigenvalues()
[130]: (array([5.24761553, 1.58768356, 0.82500567, 0.65101447, 0.5547266,
              0.47883697, 0.43628435, 0.38710866, 0.33764836, 0.27889466,
              0.21518119]),
       array([ 4.84504462e+00, 1.14420518e+00, 6.14439920e-01, 1.40485497e-01,
               1.08696311e-01, 5.11181298e-02, -2.86317525e-03, -6.33838298e-02,
              -1.53794563e-01, -2.54448799e-01, -3.04960458e-01]))
[140]: values = np.arange(1,12)
      eigenvalues = pd.DataFrame(data=fa.get_eigenvalues())
      plt.plot(values, eigenvalues.loc[0], 'o-', linewidth=2, color='blue')
      plt.title('Scree Plot')
      plt.xlabel('Factor')
      plt.ylabel('Eigenvalue')
      plt.show()
```





El número óptimo de valores propios es de dos, ya que se observa en el gráfico solamente dos factores son relevantes.

Utilizando semopy se obtiene solo un valor propio el cual se compone de distintos factores.

0.8 Latent clases

MntWines + MntGoldProds

R package adapted for Python can be used, called stepmix (install with pip)

```
NameError

Traceback (most recent call last)

ipython-input-2-e83a51807554> in <module>

6 # Fit model and predict clusters

----> 7 model.fit(df_food)

8 df_food2['pred']=model.predict(df_food2)

NameError: name 'df_food' is not defined
```

0.9 Latent growth

Latent growth modelling is not available on Python at this time. Example available in R for the lavaan library at https://lavaan.ugent.be/tutorial/growth.html

Latent trajectory class (growth curves and class membership) is not available on Python at this time. Example available in R using the LCTMtools library at https://rstudio-pubs-static.s3.amazonaws.com/522393 3aa766589868426e9c0a92d7971b619d.html.

0.10 General CFA

0.11 PREGUNTA 5

Con los resultados obtenidos en la Pregunta 4, proponga un CFA donde cada variable solo se asocia con un factor. Entregue un nombre a cada factor que representa el concepto comun entre todas las variables. Reporte la importancia de cada medida (variable) a cada factor e indique la correlacion entre factores.

Name of objective: MLW Optimization method: SLSQP Optimization successful.

Optimization terminated successfully

Objective value: 1.666 Number of iterations: 234

Params: 0.448 0.306 0.318 3.155 0.347 -802.935 -1231.049 -1268.667 718.095 1388.794 3.944 5.026 1630.062 22619.162 2.136 55967.191 5.315 2249.190 1335.237 3.499 0.000 -0.123 4972.862

```
[169]: model.inspect(mode='list', what="names", std_est=True)
[169]: lval op rval Estimate Est. Std \
```

```
0
        MntMeatProducts
                                              Mnt1
                                                                   0.424533
                                                         1.000000
1
        MntFishProducts
                                              Mnt1
                                                         0.448084
                                                                   0.616322
2
              MntFruits
                                              Mnt.1
                                                         0.305613
                                                                   0.508013
3
       MntSweetProducts
                                              Mnt1
                                                         0.317731
                                                                   0.515273
4
               MntWines
                                              Mnt.1
                                                         3.155213
                                                                   0.685109
5
           MntGoldProds
                                              Mnt1
                                                         0.347267
                                                                   0.458806
```

```
1.000000 0.000864
6
      NumDealsPurchases
                                               Num1
7
        NumWebPurchases
                                               Num1
                                                       -802.934639 -0.490585
8
    NumCatalogPurchases
                                               Num1
                                                      -1231.048853 -0.806019
9
      NumStorePurchases
                                               Num1
                                                      -1268.666541 -0.674958
10
      NumWebVisitsMonth
                                               Num1
                                                                     0.504620
                                                        718.094637
11
                    Num1
                                               Num1
                                                          0.000003
                                                                     1.000000
12
                                               Mnt1
                    Num1
                           ~ ~
                                                         -0.122759 -1.076875
13
                    Mnt1
                                               Mnt1
                                                       4972.861827
                                                                     1.000000
14
       MntSweetProducts
                                  MntSweetProducts
                                                       1388.793530
                                                                     0.734494
15
      NumWebVisitsMonth
                                 NumWebVisitsMonth
                                                                     0.745358
                                                          3.944282
16
      NumStorePurchases
                           ~ ~
                                 NumStorePurchases
                                                          5.026366
                                                                     0.544432
17
        MntFishProducts
                                   MntFishProducts
                                                       1630.061796
                                                                     0.620147
18
        MntMeatProducts
                                   MntMeatProducts
                                                      22619.162300
                                                                     0.819772
19
    NumCatalogPurchases
                               NumCatalogPurchases
                                                          2.135553
                                                                     0.350333
20
                MntWines
                                           MntWines
                                                      55967.190822
                                                                     0.530626
                           ~ ~
21
        NumWebPurchases
                                   NumWebPurchases
                                                          5.315315
                                                                     0.759326
22
           {\tt MntGoldProds}
                                       MntGoldProds
                                                       2249.189594
                                                                     0.789497
23
               MntFruits
                                          MntFruits
                                                       1335.236849
                                                                     0.741923
24
      NumDealsPurchases
                                 NumDealsPurchases
                                                          3.499456
                                                                     0.99999
        Std. Err
                     z-value
                                p-value
0
1
        0.024977
                   17.939968
                                    0.0
2
                                    0.0
        0.018659
                   16.378717
3
        0.019257
                   16.499077
                                    0.0
4
        0.168644
                   18.709316
                                    0.0
5
        0.022413
                   15.494214
                                    0.0
6
7
    20992.793033
                   -0.038248
                                0.96949
8
                   -0.038248
                                0.96949
    32185.843661
9
                   -0.038248
    33169.368209
                                0.96949
10
    18774.642528
                    0.038248
                                0.96949
11
        0.000137
                    0.019124
                               0.984742
12
        3.209545
                   -0.038248
                                0.96949
13
      500.407802
                    9.937618
                                    0.0
14
       43.748192
                   31.745164
                                    0.0
15
                   31.668377
                                    0.0
         0.12455
16
        0.170915
                   29.408488
                                    0.0
17
       53.233495
                    30.62098
                                    0.0
18
                   32.293209
                                    0.0
      700.430928
19
        0.091074
                   23.448504
                                    0.0
20
     1917.583421
                   29.186313
                                    0.0
21
                   31.771515
                                    0.0
        0.167298
22
       70.026645
                   32.119054
                                    0.0
23
       41.987765
                   31.800617
                                    0.0
24
        0.105971
                   33.022717
                                    0.0
```

```
[170]: semopy.calc_stats(model)
              DoF DoF Baseline
[170]:
                                          chi2 chi2 p-value
                                                              chi2 Baseline
                                                                                     CFI
               43
                                  3633.739501
                                                          0.0
                                                                 13645.644069 0.735793
       Value
                              55
                    GFI
                             AGFI
                                         NFI
                                                    TLI
                                                            RMSEA
                                                                          AIC
              0.733707 0.659393 0.733707 0.662061
                                                         0.195717 42.667823
                      BTC
                             LogLik
       Value
             173.481214
                          1.666089
[47]:
       semopy.semplot(model, "model.png")
        FileNotFoundError
                                                     Traceback (most recent call last)
        ~/opt/anaconda3/lib/python3.8/site-packages/graphviz/backend/execute.py in_
         Grun_check(cmd, input_lines, encoding, quiet, **kwargs)
             80
                         else:
        ---> 81
                             proc = subprocess.run(cmd, **kwargs)
             82
                     except OSError as e:
        ~/opt/anaconda3/lib/python3.8/subprocess.py in run(input, capture_output,_
         →timeout, check, *popenargs, **kwargs)
            492
        --> 493
                     with Popen(*popenargs, **kwargs) as process:
            494
                         try:
        ~/opt/anaconda3/lib/python3.8/subprocess.py in __init__(self, args, bufsize, الم
         →executable, stdin, stdout, stderr, preexec_fn, close_fds, shell, cwd, env, u
         ouniversal_newlines, startupinfo, creationflags, restore_signals,
         ⇔start_new_session, pass_fds, encoding, errors, text)
            857
        --> 858
                             self._execute_child(args, executable, preexec_fn, close_fds
            859
                                                   pass fds, cwd, env,
        ~/opt/anaconda3/lib/python3.8/subprocess.py in _execute_child(self, args,u
         ⇔executable, preexec_fn, close_fds, pass_fds, cwd, env, startupinfo, chockets, creationflags, shell, p2cread, p2cwrite, c2pread, c2pwrite, errread, errwrite
         ⇔restore signals, start new session)
           1705
                                          err_msg = os.strerror(errno_num)
        -> 1706
                                      raise child exception type(errno num, err msg,
         ⇔err filename)
           1707
                                 raise child_exception_type(err_msg)
        FileNotFoundError: [Errno 2] No such file or directory: PosixPath('dot')
        The above exception was the direct cause of the following exception:
```

```
ExecutableNotFound
                                           Traceback (most recent call last)
<ipython-input-47-65db599301fb> in <module>
---> 1 semopy.semplot(model, "model.png")
~/opt/anaconda3/lib/python3.8/site-packages/semopy/plot.py in semplot(mod,,,
 ofilename, inspection, plot covs, plot exos, images, engine, latshape,
 →plot_ests, std_ests, show)
    122
                        label = str()
    123
                    g.edge(rval, lval, label=label, dir='both', style='dashed')
--> 124
            g.render(filename, view=show)
    125
            return g
~/opt/anaconda3/lib/python3.8/site-packages/graphviz/_tools.py in wrapper(*args___
 ↔**kwargs)
    169
                                       category=category)
    170
--> 171
                    return func(*args, **kwargs)
    172
    173
                return wrapper
~/opt/anaconda3/lib/python3.8/site-packages/graphviz/rendering.py in_
 render(self, filename, directory, view, cleanup, format, renderer, formatter,
 oneato_no_op, quiet, quiet_view, outfile, engine, raise_if_result_exists, u
 ⇔overwrite_source)
    120
                args.append(filepath)
    121
--> 122
                rendered = self. render(*args, **kwargs)
    123
    124
                if cleanup:
~/opt/anaconda3/lib/python3.8/site-packages/graphviz/_tools.py in wrapper(*args___
 ↔**kwargs)
    169
                                       category=category)
    170
--> 171
                    return func(*args, **kwargs)
    172
    173
                return wrapper
~/opt/anaconda3/lib/python3.8/site-packages/graphviz/backend/rendering.py in_
 render(engine, format, filepath, renderer, formatter, neato_no_op, quiet,⊔
 ⇔outfile, raise_if_result_exists, overwrite_filepath)
    322
            cmd += args
    323
--> 324
            execute.run_check(cmd,
    325
                              cwd=filepath.parent if filepath.parent.parts else
 →None.
    326
                              quiet=quiet,
```

No logré que se pudiera ver el modelo en mi computador.

0.12 Complete SEM example

0.13 Pregunta 5

Finalmente, implemente un SEM completo usando la estructura propuesta en la Pregunta 5. En particular, estime un modelo donde los factores explican la variable Response, junto con otras variables demograficas que existen en la base de datos. Ademas utilice dichas variables relevantespara explicar los factores latentes si lo considera apropiado. Las variables a incluir en el modelo final deben tener sustento teorico y el modelo final debe optimizar el ajuste a los datos, en base a los criterios vistos en clase. Que puede concluir en base a sus resultados?

```
[174]: import semopy
       import pandas as pd
       desc = semopy.examples.political_democracy.get_model()
       print(desc)
       # measurement model
       ind60 = x1 + x2 + x3
       dem60 = y1 + y2 + y3 + y4
       dem65 = y5 + y6 + y7 + y8
       # regressions
       dem60 \sim ind60
       dem65 \sim ind60 + dem60
       # residual correlations
       y1 ~~ y5
       y2 \sim y4 + y6
       y3 ~~ y7
       y4 ~~ y8
      y6 ~~ y8
[173]: \mod = """
       # measurement model
       {\tt Mnt1} =~ {\tt MntMeatProducts} + {\tt MntFishProducts} + {\tt MntFruits} + {\tt MntSweetProducts} +
         \hookrightarrowMntWines + MntGoldProds
```

```
Num1 =~ NumDealsPurchases + NumWebPurchases + NumCatalogPurchases +<sub>\perp</sub>
\( \text{NumStorePurchases} + \text{NumWebVisitsMonth} \)

# regressions

Response ~ Mnt1 + Num1 + Income + Kidhome + education_2n Cycle +<sub>\perp</sub>
\( \text{education_Basic} + \text{education_Graduation} + \text{education_Master} + \text{education_PhD} +<sub>\perp</sub>
\( \text{Recency} \)

# residual correlations

"""

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

```
Traceback (most recent call last):
 File "/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/semopy/
 →parser.py", line 189, in parse_desc
   kind, items = separate_token(line)
 File "/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/semopy/
 →parser.py", line 57, in separate_token
    raise SyntaxError(f'Invalind syntax for line:\n{token}')
 File "<string>", line unknown
SyntaxError: Invalind syntax for line:
Response ~ Mnt1 + Num1 + Kidhome + education 2n Cycle + education Basic + L
 →education_Graduation + education_Master + education_PhD + Recency
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
 File "/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/IPython/cor/
 ⇔interactiveshell.py", line 3437, in run_code
    exec(code_obj, self.user_global_ns, self.user_ns)
 File "<ipython-input-173-847abba67dd2>", line 12, in <module>
   model = semopy.Model(mod)
 File "/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/semopy/mode".

¬py", line 105, in __init__
    super().__init__(description)
```

```
File "/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/semopy/

model_base.py", line 53, in __init__
effects, operations = parse_desc(description)

File "/Users/macbookair/opt/anaconda3/lib/python3.8/site-packages/semopy/
parser.py", line 203, in parse_desc
raise SyntaxError(f"Syntax error for line:\n{line}")

File "<string>", line unknown

SyntaxError: Syntax error for line:
Response ~ Mnt1 + Num1 + Kidhome + education_2n Cycle + education_Basic +_u
education_Graduation + education_Master + education_PhD + Recency

data = semopy.examples.political_democracy.get_data()
mod = semopy.Model(desc)
res = mod.fit(data)
```

[178]: print(mod.inspect())

```
p-value
    lval op
               rval Estimate Std. Err
                                           z-value
0
    dem60
              ind60
                     1.482379
                               0.399024
                                          3.715017
                                                    0.000203
1
   dem65
              ind60
                     0.571912 0.221383
                                          2.583364
                                                    0.009784
2
    dem65
              dem60 0.837574 0.098446
                                          8.507992
                                                         0.0
3
              ind60
                     1.000000
      x1
4
      x2
              ind60 2.180494 0.138565
                                         15.736254
                                                         0.0
5
       xЗ
              ind60 1.818546 0.151993
                                          11.96465
                                                         0.0
6
              dem60 1.000000
      y1
7
      у2
              dem60
                     1.256819 0.182687
                                          6.879647
                                                         0.0
8
      yЗ
              dem60
                     1.058174 0.151521
                                                         0.0
                                          6.983699
9
       y4
                     1.265186 0.145151
                                          8.716344
                                                         0.0
              dem60
10
      у5
              dem65
                     1.000000
                                                         0.0
11
      у6
              dem65
                     1.185743 0.168908
                                          7.020032
12
       y7
              dem65
                     1.279717
                               0.159996
                                           7.99841
                                                         0.0
13
      у8
              dem65
                     1.266084 0.158238
                                          8.001141
                                                         0.0
14
   dem60
              dem60
                     3.950849 0.920451
                                          4.292296
                                                    0.000018
15
              dem65
                     0.172210 0.214861
                                          0.801494
                                                    0.422846
   dem65
16
   ind60
          ~ ~
              ind60
                     0.448321 0.086677
                                          5.172345
                                                         0.0
17
                 y5 0.624423 0.358435
                                          1.742083 0.081494
      y1
18
      y1
          ~ ~
                 y1
                     1.892743
                                0.44456
                                          4.257565
                                                    0.000021
19
      y2
                 y4 1.319589
                                0.70268
                                          1.877937
                                                     0.06039
20
      y2
                 y6 2.156164 0.734155
                                          2.936934
                                                    0.003315
                 y2 7.385292 1.375671
21
      у2
          ~ ~
                                          5.368501
                                                         0.0
22
                 y7 0.793329 0.607642
      уЗ
                                          1.305585 0.191694
23
      yЗ
                 y3 5.066628 0.951722
                                          5.323646
                                                         0.0
          ~ ~
24
                 y8 0.347222 0.442234
                                          0.785154 0.432363
       y4
          ~ ~
25
                 y4 3.147911 0.738841
                                          4.260605
                                                     0.00002
       y4
```

```
26
                  v8 1.357037
                                  0.5685
                                           2.387047 0.016984
       v6
27
      y6
          ~ ~
                  y6 4.954364 0.914284
                                           5.418843
                                                          0.0
28
       x2
                     0.119894 0.069747
                                           1.718973
                                                    0.085619
                  x2
          ~ ~
29
      y5
                  y5 2.351910 0.480369
                                           4.896044
                                                    0.000001
30
       x1
          ~ ~
                  x1 0.081573 0.019495
                                           4.184317
                                                    0.000029
                  x3 0.466732 0.090168
                                           5.176276
31
       xЗ
                                                          0.0
32
       8y
                  y8 3.256389
                                0.69504
                                           4.685182 0.000003
33
       y7
                  v7 3.430032 0.712732
                                           4.812512 0.000001
```

[51]: semopy.semplot(mod, "semmodel.png")

```
FileNotFoundError
                                            Traceback (most recent call last)
~/opt/anaconda3/lib/python3.8/site-packages/graphviz/backend/execute.py in_
 Grun check(cmd, input lines, encoding, quiet, **kwargs)
                else:
---> 81
                     proc = subprocess.run(cmd, **kwargs)
     82
            except OSError as e:
~/opt/anaconda3/lib/python3.8/subprocess.py in run(input, capture_output,_
 →timeout, check, *popenargs, **kwargs)
    492
--> 493
            with Popen(*popenargs, **kwargs) as process:
    494
                 trv:
~/opt/anaconda3/lib/python3.8/subprocess.py in __init__(self, args, bufsize,__
 ⊶executable, stdin, stdout, stderr, preexec_fn, close_fds, shell, cwd, env,⊔
 ouniversal_newlines, startupinfo, creationflags, restore_signals, ⊔
 ⇔start_new_session, pass_fds, encoding, errors, text)
    857
--> 858
                     self. execute child(args, executable, preexec fn, close fds
    859
                                          pass_fds, cwd, env,
~/opt/anaconda3/lib/python3.8/subprocess.py in _execute_child(self, args,_
 ⇔executable, preexec_fn, close_fds, pass_fds, cwd, env, startupinfo, correctionflags, shell, p2cread, p2cwrite, c2pread, c2pwrite, errread, errwrite
 →restore_signals, start_new_session)
   1705
                                 err_msg = os.strerror(errno_num)
-> 1706
                             raise child_exception_type(errno_num, err_msg,__
 1707
                         raise child_exception_type(err_msg)
FileNotFoundError: [Errno 2] No such file or directory: PosixPath('dot')
The above exception was the direct cause of the following exception:
ExecutableNotFound
                                            Traceback (most recent call last)
<ipython-input-51-b1f1c8bae510> in <module>
```

```
---> 1 semopy.semplot(mod, "semmodel.png")
 ~/opt/anaconda3/lib/python3.8/site-packages/semopy/plot.py in semplot(mod, __
  ofilename, inspection, plot_covs, plot_exos, images, engine, latshape,
  ⇔plot ests, std ests, show)
     122
                         label = str()
     123
                     g.edge(rval, lval, label=label, dir='both', style='dashed')
 --> 124
             g.render(filename, view=show)
     125
             return g
 ~/opt/anaconda3/lib/python3.8/site-packages/graphviz/_tools.py in wrapper(*args___
  →**kwargs)
     169
                                        category=category)
     170
 --> 171
                     return func(*args, **kwargs)
     172
     173
                 return wrapper
 ~/opt/anaconda3/lib/python3.8/site-packages/graphviz/rendering.py in_
  orender(self, filename, directory, view, cleanup, format, renderer, formatter,
  oneato_no_op, quiet, quiet_view, outfile, engine, raise_if_result_exists, u
  ⇔overwrite_source)
     120
                 args.append(filepath)
     121
 --> 122
                 rendered = self. render(*args, **kwargs)
     123
     124
                 if cleanup:
 ~/opt/anaconda3/lib/python3.8/site-packages/graphviz/_tools.py in wrapper(*args___
  ↔**kwargs)
     169
                                        category=category)
     170
 --> 171
                     return func(*args, **kwargs)
     172
     173
                 return wrapper
 ~/opt/anaconda3/lib/python3.8/site-packages/graphviz/backend/rendering.py in_
  render(engine, format, filepath, renderer, formatter, neato_no_op, quiet,⊔
  ⇔outfile, raise_if_result_exists, overwrite_filepath)
     322
             cmd += args
     323
 --> 324
             execute.run_check(cmd,
     325
                               cwd=filepath.parent if filepath.parent.parts else
  →None,
     326
                               quiet=quiet,
 ~/opt/anaconda3/lib/python3.8/site-packages/graphviz/backend/execute.py in___
  →run_check(cmd, input_lines, encoding, quiet, **kwargs)
```

```
82 except OSError as e:
83 if e.errno == errno.ENOENT:
---> 84 raise ExecutableNotFound(cmd) from e
85 raise
86

ExecutableNotFound: failed to execute PosixPath('dot'), make sure the Graphviz
⇔executables are on your systems' PATH
```

Tarea 3

Instrucciones

Los resultados de los ejericicios propuestos se deben entregar como un notebook por correo electronico a juancaros@udec.cl el dia 9/6 hasta las 21:00. Es importante considerar que el código debe poder ejecutarse en cualquier computadora con la data original del repositorio. Recordar la convencion para el nombre de archivo ademas de incluir en su documento titulos y encabezados por seccion. Utilizar la base de datos ifood_df.csv.

Como se indica en la Tabla 1, las variables describen el comportamiento de un set de consumidores en una tienda de retail. Las variables categoricas (e.g. educacion, estado civil) ya han sido convertidas a variables binarias (una por cada categoria).

```
[8]: Image(filename='../data/dictionary.png', width=600)
```

[8]:

Feature	Description
AcceptedCmp1	1 if costumer accepted the offer in the 1 st campaign, 0 otherwise
AcceptedCmp2	1 if costumer accepted the offer in the 2 nd campaign, 0 otherwise
AcceptedCmp3	1 if costumer accepted the offer in the 3 rd campaign, 0 otherwise
AcceptedCmp4	1 if costumer accepted the offer in the 4 th campaign, 0 otherwise
AcceptedCmp5	1 if costumer accepted the offer in the 5 th campaign, 0 otherwise
Response (target)	1 if costumer accepted the offer in the last campaign, 0 otherwise
Complain	1 if costumer complained in the last 2 years
DtCustomer	date of customer's enrollment with the company
Education	customer's level of education
Marital	customer's marital status
Kidhome	number of small children in customer's household
Teenhome	number of teenagers in customer's household
Income	customer's yearly household income
MntFishProducts	amount spent on fish products in the last 2 years
MntMeatProducts	amount spent on meat products in the last 2 years
MntFruits	amount spent on fruits in the last 2 years
MntSweetProducts	amount spent on sweet products in the last 2 years
MntWines	amount spent on wines in the last 2 years
MntGoldProds	amount spent on gold products in the last 2 years
NumDealsPurchases	number of purchases made with discount
NumCatalogPurchases	number of purchases made using catalogue
NumStorePurchases	number of purchases made directly in stores
NumWebPurchases	number of purchases made through company's web site
NumWebVisitsMonth	number of visits to company's web site in the last month
Recency	number of days since the last purchase

Table 1: Meta-data table

1 Anexo 1: analisis de la información

- AcceptedCmp1 = 1 si el cliente aceptó la oferta en la 1ra campaña, 0 de lo contrario
- AcceptedCmp2 = 1 si el cliente aceptó la oferta en la 2da campaña, 0 de lo contrario
- AcceptedCmp3 = 1 si el cliente aceptó la oferta en la 3ra campaña, 0 de lo contrario
- AcceptedCmp4 = 1 si el cliente aceptó la oferta en la 4ta campaña, 0 de lo contrario
- AcceptedCmp5 = 1 si el cliente aceptó la oferta en la 5ta campaña, 0 de lo contrario
- Response (target) = 1 si el cliente aceptó la oferta en la última campaña, 0 de lo contrario
- Complain = 1 si el cliente se quejó en los últimos 2 años
- DtCustomer = fecha de inscripción del cliente en la empresa
- Education = nivel de educación del cliente
- Marital = estado civil
- Kidhome = número de niños pequeños en el hogar
- Teenhome = número de adolescentes en el hogar
- Income = ingresos familiares anuales
- MntFishProducts = cantidad gastada en pescados (productos del mar) en los últimos 2 años
- MntMeatProducts = cantidad gastada en carne en los últimos 2 años
- MntFruits = cantidad gastada en frutas en los últimos 2 años

- MntSweetProducts = cantidad gastada en productos dulces en los últimos 2 años
- MntWines = cantidad gastada en vino en los últimos 2 años
- MntGoldProds = cantidad gastada en productos de "lujo" en los últimos 2 años
- NumDealsPurchases = número de compras realizadas con descuento
- NumCatalogPurchases = número de compras realizadas utilizando el catálogo
- NumStorePurchases = número de compras realizadas directamente en las tiendas
- NumWebPurchases = número de compras realizadas a través del sitio web de la empresa
- NumWebVisitsMonth = número de visitas al sitio web de la empresa en el último mes
- Recency = número de días desde la última compra

```
[71]: # Check for missing data
print("Valores de Null en el Dataframe:")
print(df_food.isnull().sum())
```

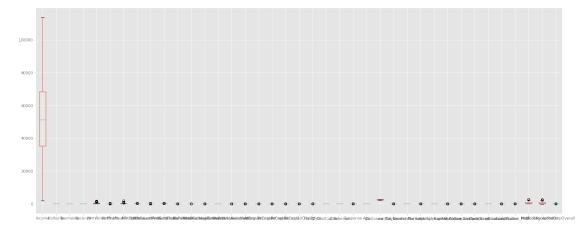
Valores de Null en el Dataframe: Income 0 0 Kidhome 0 Teenhome Recency 0 0 MntWines 0 MntFruits MntMeatProducts 0 MntFishProducts 0 0 MntSweetProducts MntGoldProds 0 0 NumDealsPurchases NumWebPurchases 0 0 NumCatalogPurchases NumStorePurchases 0 NumWebVisitsMonth 0 0 AcceptedCmp3 AcceptedCmp4 0 AcceptedCmp5 0 0 AcceptedCmp1 AcceptedCmp2 0 Complain 0 $Z_CostContact$ 0 Z_Revenue 0 0 Response Age 0 Customer_Days 0 0 marital_Divorced 0 marital_Married marital_Single 0 marital_Together 0 marital_Widow 0 education_2n Cycle 0 education Basic

```
education_Graduation 0
education_Master 0
education_PhD 0
MntTotal 0
MntRegularProds 0
AcceptedCmpOverall 0
dtype: int64
```

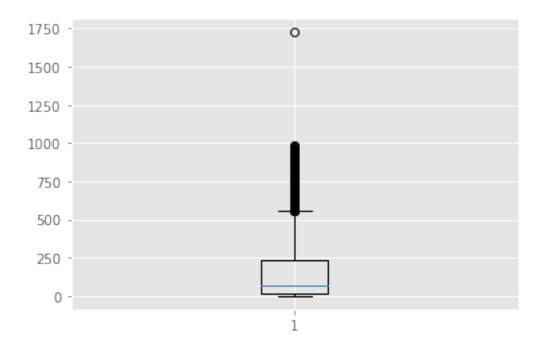
```
[72]: # Create a figure and axis
fig, ax = plt.subplots(figsize=(25, 10))

# Plot the box plots for all columns
df_food.boxplot(ax=ax)

# Show the plot
plt.show()
```

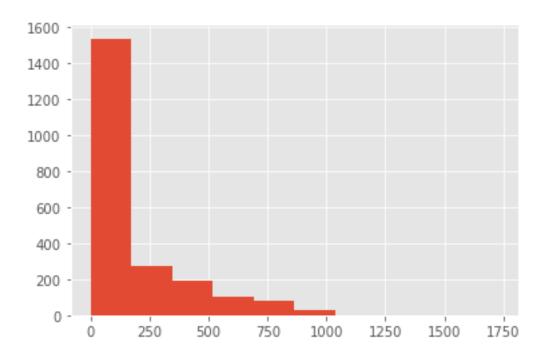


```
[73]: plt.boxplot(df_food['MntMeatProducts'])
   plt.show()
```

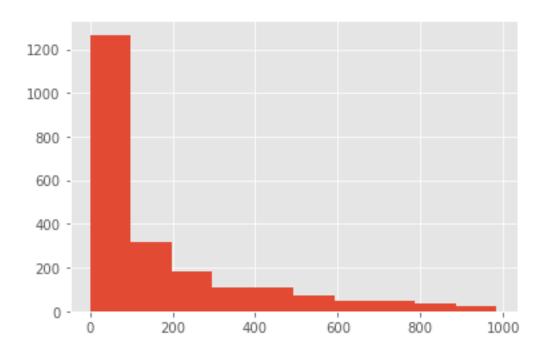


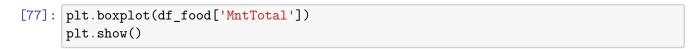
1725

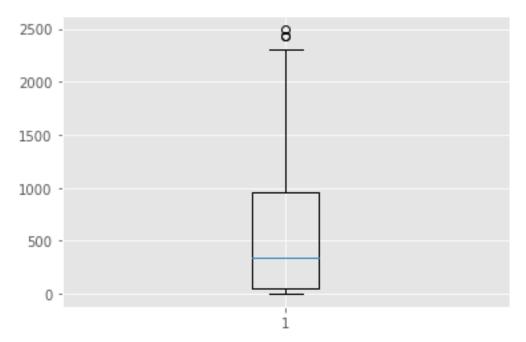
Length: 551, dtype: int64



```
[75]: MntMeatProducts
             53
      5
              49
      11
             49
      8
              44
      6
              42
              . .
      444
               1
      450
               1
      452
               1
      454
               1
      984
               1
      Length: 549, dtype: int64
```

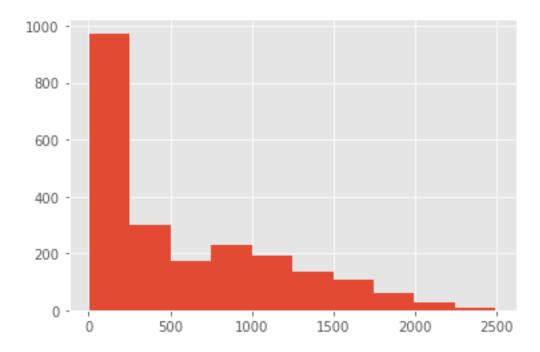






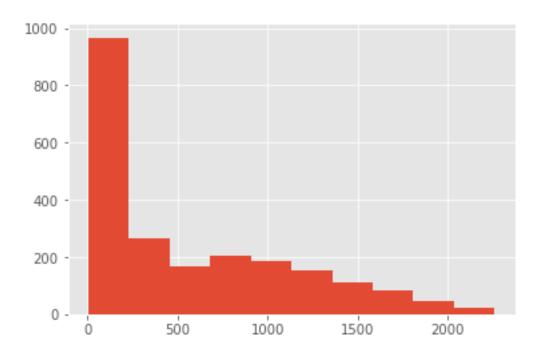
```
[78]: A="MntTotal"
  plt.style.use('ggplot')
  df_food['MntTotal'].hist();
  df_food.value_counts(A)
```

```
[78]: MntTotal
      39
              30
      41
              25
      19
              24
      40
              24
              24
      16
      841
                1
      839
                1
      836
      826
                1
      2491
                1
      Length: 896, dtype: int64
```



```
[79]: df_food = df_food[(df_food["MntTotal"] <2300) & (df_food["MntTotal"] > 0)];
    print(len(df_food));
    A="MntTotal"
    plt.style.use('ggplot')
    df_food['MntTotal'].hist();
    df_food.value_counts(A)
```

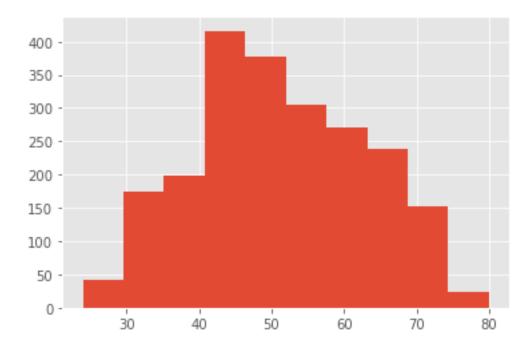
```
[79]: MntTotal
      39
              30
              25
      41
      40
              24
      19
              24
              24
      16
      841
               1
      839
               1
      836
               1
      826
               1
      2262
               1
     Length: 893, dtype: int64
```



```
[80]: A="Age"
  plt.style.use('ggplot')
  df_food['Age'].hist();
  df_food.value_counts(A)
```

[80]: Age
44 88
49 85
45 81
48 78

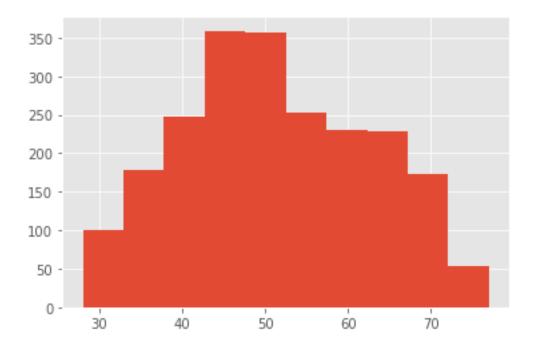
```
27 5
26 3
24 2
79 1
80 1
dtype: int64
```



```
[81]: df_food = df_food[(df_food["Age"] < 78) & (df_food["Age"] > 27)];
print(len(df_food));
A="Age"
plt.style.use('ggplot')
df_food['Age'].hist();
df_food.value_counts(A)
```

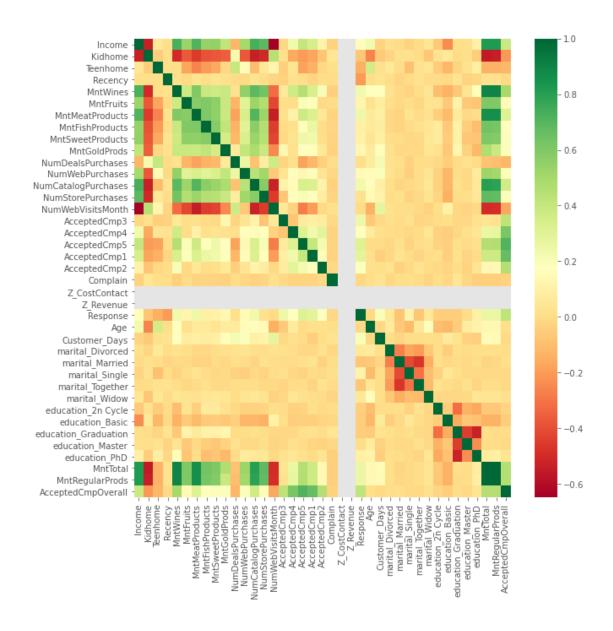
```
[81]: Age
      44
             88
      49
             85
      45
             81
      48
             78
      42
             76
      50
            74
             74
      55
      47
             71
      51
             69
```

```
46
      69
64
      55
41
      52
      52
62
68
      52
52
      51
61
      50
      50
54
43
      50
60
      49
66
      49
65
      48
58
      44
      44
57
53
      44
38
      43
69
      42
34
      41
63
      41
56
      41
37
      41
40
      39
36
      38
39
      38
59
      35
67
      35
35
      32
71
      29
31
      29
70
      29
32
      28
33
      27
72
      21
30
      18
74
      16
73
      16
28
      13
29
      13
75
       8
76
       7
77
       6
dtype: int64
```



```
[82]: fig, ax = plt.subplots(1,1, figsize = (10,10))
sns.heatmap(df_food.corr(), cmap='RdYlGn')
```

[82]: <AxesSubplot:>



[]: