In [759…
```python
import pandas as pd
import matplotlib as plt
import numpy as np
from numpy import unique
```

Creamos un dataframe en el cual se excluyen de por si columnas que no tienen nada de informacion.

In [760…
```python
df  = pd.read_csv('small_train.csv')

df1 = df.dropna(how='all', axis=1)

df1
```

Out[760…

	Id	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var9	Var10	...	Var221	Var222	Var223	Var224	Var225	Var226	Var227	Var228	Var229	Target
0	1	NaN	NaN	NaN	NaN	NaN	1526.0	7.0	NaN	NaN	...	oslk	fXVEsaq	jySVZNlOJy	NaN	NaN	xb3V	RAYp	F2FyR07IdsN7I	NaN	-1
1	2	NaN	NaN	NaN	NaN	NaN	525.0	0.0	NaN	NaN	...	oslk	2Kb5FSF	LM8l689qOp	NaN	NaN	fKCe	RAYp	F2FyR07IdsN7I	NaN	-1
2	3	NaN	NaN	NaN	NaN	NaN	5236.0	7.0	NaN	NaN	...	Al6ZaUT	NKv4yOc	jySVZNlOJy	NaN	kG3k	Qu4f	02N6s8f	ib5G6X1eUxUn6	am7c	-1
3	4	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	...	oslk	CE7uk3u	LM8l689qOp	NaN	NaN	FSa2	RAYp	F2FyR07IdsN7I	NaN	-1
4	5	NaN	NaN	NaN	NaN	NaN	1029.0	7.0	NaN	NaN	...	oslk	1J2cvxe	LM8l689qOp	NaN	kG3k	FSa2	RAYp	F2FyR07IdsN7I	mj86	-1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
49995	49996	NaN	NaN	NaN	NaN	NaN	357.0	0.0	NaN	NaN	...	oslk	EROH7Cg	LM8l689qOp	NaN	NaN	7FJQ	RAYp	F2FyR07IdsN7I	NaN	-1
49996	49997	NaN	NaN	NaN	NaN	NaN	1078.0	0.0	NaN	NaN	...	oslk	GfSQowC	LM8l689qOp	NaN	kG3k	FSa2	RAYp	55YFVY9	am7c	-1
49997	49998	NaN	NaN	NaN	NaN	NaN	2807.0	7.0	NaN	NaN	...	oslk	dh6qI2t	LM8l689qOp	NaN	ELof	fKCe	RAYp	TCU50_Yjmm6GIBZ0lL_	NaN	-1
49998	49999	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	NaN	...	oslk	2fF2Oqu	LM8l689qOp	NaN	NaN	FSa2	RAYp	F2FyR07IdsN7I	NaN	-1
49999	50000	NaN	NaN	NaN	NaN	NaN	1694.0	7.0	NaN	NaN	...	oslk	IIvC99a	LM8l689qOp	NaN	NaN	xb3V	RAYp	F2FyR07IdsN7I	NaN	1

50000 rows × 214 columns

Ahora analizamos la data en sus partes numerica y categorica. Cada una separada por resultados de 1 y -1

In [761…
```python
numerical_data = df1.loc[:, "Var1":"Var190"]
numerical_target_data = numerical_data.join(df1["Target"])
df_numerical_t1 = numerical_target_data.loc[numerical_target_data.loc[:,"Target"]==1]
df_numerical_t1.describe()
```

Out[761…

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var9	Var10	Var11	...	Var181	Var182	Var183	Var184	Var186	Var187	
count	22.000000	30.0	30.000000	47.0	8.500000e+01	3476.000000	3461.000000	22.000000	8.500000e+01	30.000000	...	3498.000000	4.700000e+01	3.000000e+01	30.000000	22.000000	22.00000	30.
mean	21.090909	0.0	4371.400000	0.0	2.093672e+05	1466.443613	7.461138	142.636364	2.288987e+05	9.066667	...	0.608348	1.139278e+06	9.811920e+04	2.533333	2.454545	41.00000	121.
std	76.117021	0.0	23853.665323	0.0	4.477857e+05	2351.148475	6.291430	483.326720	4.663292e+05	4.570772	...	2.565105	1.740722e+06	2.394277e+05	4.980883	4.404838	133.53045	106.
min	0.000000	0.0	0.000000	0.0	0.000000e+00	0.000000	0.000000	0.000000	0.000000e+00	8.000000	...	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.00000	0.
25%	0.000000	0.0	0.000000	0.0	0.000000e+00	609.000000	7.000000	10.000000	0.000000e+00	8.000000	...	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.50000	17.
50%	0.000000	0.0	0.000000	0.0	0.000000e+00	952.000000	7.000000	30.000000	0.000000e+00	8.000000	...	0.000000	5.095620e+05	0.000000e+00	0.000000	0.000000	6.00000	148.
75%	8.000000	0.0	0.000000	0.0	1.967300e+05	1660.750000	7.000000	73.500000	2.439360e+05	8.000000	...	0.000000	1.377453e+06	5.652700e+04	4.000000	6.000000	20.00000	185.
max	360.000000	0.0	130668.000000	0.0	2.592000e+06	68439.000000	35.000000	2300.000000	2.332800e+06	32.000000	...	28.000000	7.200840e+06	1.209600e+06	20.000000	18.000000	634.00000	412.

8 rows × 175 columns

In [762…
```python
numerical_data = df1.loc[:, "Var1":"Var190"]
numerical_target_data = numerical_data.join(df1["Target"])
df_numerical_tn = numerical_target_data.loc[numerical_target_data.loc[:,"Target"]==-1]
df_numerical_tn.describe()
```

Out[762…

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var9	Var10	Var11	...	Var181	Var182	Var183	Var184	V
count	680.000000	1211.000000	1210.000000	1532.000000	1.402000e+03	40995.000000	41000.000000	680.000000	1.402000e+03	1210.000000	...	41493.000000	1.532000e+03	1.211000e+03	1211.000000	680.0
mean	11.176471	0.004129	327.461157	0.129243	2.405774e+05	1314.565849	6.754488	45.088235	4.025126e+05	8.614876	...	0.611718	1.425147e+06	7.726978e+04	8.607762	3.3
std	39.098886	0.143681	2154.679029	1.294719	6.542114e+05	2711.855948	6.325972	131.182470	9.478455e+05	2.816490	...	2.489772	2.294233e+06	2.006827e+05	47.536890	8.8
min	0.000000	0.000000	0.000000	0.000000	0.000000e+00	0.000000	0.000000	0.000000	0.000000e+00	8.000000	...	0.000000	0.000000e+00	0.000000e+00	0.000000	0.0
25%	0.000000	0.000000	0.000000	0.000000	0.000000e+00	511.000000	0.000000	4.000000	0.000000e+00	8.000000	...	0.000000	0.000000e+00	0.000000e+00	0.000000	0.0
50%	0.000000	0.000000	0.000000	0.000000	0.000000e+00	854.000000	7.000000	20.000000	0.000000e+00	8.000000	...	0.000000	1.125990e+05	0.000000e+00	0.000000	0.0
75%	16.000000	0.000000	0.000000	0.000000	1.131750e+05	1410.500000	7.000000	46.000000	2.647958e+05	8.000000	...	0.000000	1.876194e+06	4.842900e+04	8.000000	1.5
max	680.000000	5.000000	42588.000000	27.000000	6.048550e+06	131761.000000	140.000000	2098.000000	1.230000e+07	40.000000	...	49.000000	1.199478e+07	3.048400e+06	1200.000000	102.0

8 rows × 175 columns

In [763…
```python
categorical_data = df1.loc[:, "Var191":"Target"]
df_categorical_t1 = categorical_data.loc[categorical_data.loc[:,"Target"]==1]
df_categorical_t1.describe(include='all')
```

Out[763…

	Var191	Var192	Var193	Var194	Var195	Var196	Var197	Var198	Var199	Var200	...	Var221	Var222	Var223	Var224	Var225	Var226	Var227	Var228	Var229	Target
count	39	3666	3682	959	3682	3682	3675	3682	3682	2173	...	3682	3682	3423	18	2160	3682	3682	3682	1930	3682.0
unique	1	224	31	3	11	2	155	1281	923	2060	...	7	1281	4	1	3	23	7	25	4	NaN
top	r__I	vAsTmBfHUn	RO12	SEuy	taul	1K8T	lK27	fhk21Ss	r83_sZi	QK29mKO	...	oslk	catzS2D	LM8l689qOp	4n2X	ELof	Qu4f	RAYp	F2FyR07IdsN7I	am7c	NaN
freq	39	47	2486	937	3541	3657	335	377	82	4	...	2572	377	2879	18	1201	433	2432	2201	1030	NaN
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0

11 rows × 39 columns

In [764…
```python
categorical_data = df1.loc[:, "Var191":"Target"]
df_categorical_tn = categorical_data.loc[categorical_data.loc[:,"Target"]==-1]
df_categorical_tn.describe(include='all')
```

Out[764…

	Var191	Var192	Var193	Var194	Var195	Var196	Var197	Var198	Var199	Var200	...	Var221	Var222	Var223	Var224	Var225	Var226	Var227	Var228	Var229	Target
count	1044	45965	46318	11825	46318	46318	46182	46318	46314	22419	...	46318	46318	41366	802	21696	46318	46318	46318	19638	46318.0
unique	1	360	51	3	23	4	223	4118	4865	14487	...	7	4118	4	1	3	23	7	30	4	NaN
top	r__I	1GdOj1KXzC	RO12	SEuy	taul	1K8T	0Xwj	fhk21Ss	r83_sZi	yP09M03	...	oslk	catzS2D	LM8l689qOp	4n2X	ELof	FSa2	RAYp	F2FyR07IdsN7I	am7c	NaN
freq	1044	354	33478	11630	44417	45893	4299	4064	873	73	...	34437	4064	33729	802	9871	7658	32724	30502	10659	NaN
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-1.0
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-1.0
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-1.0
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-1.0
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-1.0
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-1.0

11 rows × 39 columns

Ahora analizamos si no hay alguna variable que pertenezca a solo una de estas cuatro divisiones. Esto es, quitando columnas que no tengan absolutamente ningun valor en alguna de las cuatro dataframes que hemos creado. Como ya hemos quitado columnas que no tenian ningun valor en todo el dataframe, si una columna fuera a no tener un valor en algunos de estas divisiones, significaría que se presenta solo en una instancia de compra o no compra.

Sin embargo, encontramos que no hay variables que solo pertenezcan, por ejemplo, al data frame numerico de puros compradores. Y asi para los otros tres data frames.Sabemos entonces que no hay una variable que ocurra solo cuando el cliente compro o solo cuando el cliente no compro. Podemos entonces seguir a limpiar el data frame inicial completo.

In [765…
```python
just_in_nt1 = df_numerical_t1.dropna(how='all', axis=1)
just_in_ntn = df_numerical_tn.dropna(how='all', axis=1)
just_in_ct1 = df_categorical_t1.dropna(how='all', axis=1)
just_in_ctn = df_categorical_tn.dropna(how='all', axis=1)
```

Ahora entonces limpiamos el df inicial de columnas de las cuales no se sepa mucho, esto es, que tengan un conteo muy bajo. Así como columnas que tengan un unique value de 1. Así como filas que no tengan tanta informacion, se busca tener el dataframe mas completo y rico en informacion para despues poder analizar cuales son las variables de mas peso.

In [766…
```python
df1.describe()
```

Out[766…

	Id	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var9	Var10	...	Var181	Var182	Var183	Var184	
count	50000.000000	702.000000	1241.000000	1240.000000	1579.000000	1.487000e+03	44471.000000	44461.000000	702.000000	1.487000e+03	...	44991.000000	1.579000e+03	1.241000e+03	1241.000000	702
mean	25000.500000	11.487179	0.004029	425.298387	0.125396	2.387933e+05	1326.437116	6.809496	48.145299	3.925884e+05	...	0.611456	1.416638e+06	7.777380e+04	8.460919	3
std	14433.901067	40.709951	0.141933	4270.193518	1.275481	6.441259e+05	2685.693668	6.326053	154.777855	9.278684e+05	...	2.495681	2.279786e+06	2.016188e+05	46.973777	8
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000e+00	0.000000	0.000000	0.000000	0.000000e+00	...	0.000000	0.000000e+00	0.000000e+00	0.000000	0
25%	12500.750000	0.000000	0.000000	0.000000	0.000000	0.000000e+00	518.000000	0.000000	4.000000	0.000000e+00	...	0.000000	0.000000e+00	0.000000e+00	0.000000	0
50%	25000.500000	0.000000	0.000000	0.000000	0.000000	0.000000e+00	861.000000	7.000000	20.000000	0.000000e+00	...	0.000000	1.167780e+05	0.000000e+00	0.000000	0
75%	37500.250000	16.000000	0.000000	0.000000	0.000000	1.187425e+05	1428.000000	7.000000	46.000000	2.628630e+05	...	0.000000	1.844952e+06	4.881000e+04	8.000000	6
max	50000.000000	680.000000	5.000000	130668.000000	27.000000	6.048550e+06	131761.000000	140.000000	2300.000000	1.230000e+07	...	49.000000	1.199478e+07	3.048400e+06	1200.000000	102

8 rows × 176 columns

In [767…
```python
low_colcount_arr = []

for column in df1.columns:
   if (df1[column].count()) <= 12000:
      low_colcount_arr.append(column)


df2 = df1.drop(low_colcount_arr, axis=1)

df3 = df2.dropna(thresh=44)

df3
```

Out[767…

	Id	Var6	Var7	Var13	Var21	Var22	Var24	Var25	Var28	Var35	...	Var220	Var221	Var222	Var223	Var225	Var226	Var227	Var228	Var229	Target
0	1	1526.0	7.0	184.0	464.0	580.0	14.0	128.0	166.56	0.0	...	1YVfGrO	oslk	fXVEsaq	jySVZNlOJy	NaN	xb3V	RAYp	F2FyR07IdsN7I	NaN	-1
1	2	525.0	0.0	0.0	168.0	210.0	2.0	24.0	353.52	0.0	...	0AJo2f2	oslk	2Kb5FSF	LM8l689qOp	NaN	fKCe	RAYp	F2FyR07IdsN7I	NaN	-1
2	3	5236.0	7.0	904.0	1212.0	1515.0	26.0	816.0	220.08	0.0	...	JFM1BiF	Al6ZaUT	NKv4yOc	jySVZNlOJy	kG3k	Qu4f	02N6s8f	ib5G6X1eUxUn6	am7c	-1
3	4	NaN	0.0	0.0	NaN	0.0	NaN	0.0	22.08	0.0	...	L91KIiz	oslk	CE7uk3u	LM8l689qOp	NaN	FSa2	RAYp	F2FyR07IdsN7I	NaN	-1
4	5	1029.0	7.0	3216.0	64.0	80.0	4.0	64.0	200.00	0.0	...	OrnLfvc	oslk	1J2cvxe	LM8l689qOp	kG3k	FSa2	RAYp	F2FyR07IdsN7I	mj86	-1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
49994	49995	266.0	0.0	0.0	792.0	990.0	18.0	432.0	336.56	0.0	...	kH5eMLh	oslk	dclJEx2	LM8l689qOp	NaN	xb3V	RAYp	F2FyR07IdsN7I	NaN	-1
49995	49996	357.0	0.0	0.0	132.0	165.0	2.0	0.0	288.08	0.0	...	3JmRJnY	oslk	EROH7Cg	LM8l689qOp	NaN	7FJQ	RAYp	F2FyR07IdsN7I	NaN	-1
49996	49997	1078.0	0.0	2736.0	380.0	475.0	2.0	88.0	166.56	0.0	...	MMTv4zN	oslk	GfSQowC	LM8l689qOp	kG3k	FSa2	RAYp	55YFVY9	am7c	-1
49997	49998	2807.0	7.0	1460.0	568.0	710.0	4.0	328.0	166.56	0.0	...	FM28hdx	oslk	dh6qI2t	LM8l689qOp	ELof	fKCe	RAYp	TCU50_Yjmm6GIBZ0lL_	NaN	-1
49999	50000	1694.0	7.0	828.0	192.0	240.0	0.0	48.0	220.08	5.0	...	ot6oLzk	oslk	IIvC99a	LM8l689qOp	NaN	xb3V	RAYp	F2FyR07IdsN7I	NaN	1

44991 rows × 78 columns

In [768…
```python
target_1_df1 = df3.loc[df3.loc[:,"Target"]==1]
target_percentage_df1 = (target_1_df1.shape[0]/df1.shape[0])*100
target_percentage_df1
```

Out[768…
```
6.9959999999999996
```

In [769…
```python
target_1_df3 = df3.loc[df3.loc[:,"Target"]==1]

target_percentage_df3 = (target_1_df3.shape[0]/df3.shape[0])*100
target_percentage_df3
```

Out[769…
```
7.774888310995533
```

Despues de limpiar el dataframe en base a conteo bajo por columna y fila asi como valores unicos. Ahora tenemos un dataframe de solo 78 columnas x 44991 filas. Con un conteo de valores aceptable, ya que bajo nuestro porcentage de target_1 un 0.8% solamente, por columna y fila. Asi como ninguna columna con un valor unico de 1. Es decir, todas tienen mas de un valor diferente.

Analizamos la parte numerica del dataframe resultante.

In [770…
```python
numerical_data_clean = df3.loc[:, "Var6":"Var189"].join(df3["Target"])
numerical_data_clean
```

Out[770…

	Var6	Var7	Var13	Var21	Var22	Var24	Var25	Var28	Var35	Var38	...	Var143	Var144	Var149	Var153	Var160	Var163	Var173	Var181	Var189	Target
0	1526.0	7.0	184.0	464.0	580.0	14.0	128.0	166.56	0.0	3570.0	...	0.0	9.0	397579.0	1812252.0	142.0	38418.0	0.0	0.0	462.0	-1
1	525.0	0.0	0.0	168.0	210.0	2.0	24.0	353.52	0.0	4764966.0	...	0.0	9.0	278334.0	10439160.0	32.0	238572.0	0.0	0.0	NaN	-1
2	5236.0	7.0	904.0	1212.0	1515.0	26.0	816.0	220.08	0.0	5883894.0	...	0.0	36.0	320565.0	9826360.0	206.0	434946.0	0.0	0.0	NaN	-1
3	NaN	0.0	0.0	NaN	0.0	NaN	0.0	22.08	0.0	0.0	...	0.0	NaN	NaN	0.0	0.0	0.0	0.0	0.0	NaN	-1
4	1029.0	7.0	3216.0	64.0	80.0	4.0	64.0	200.00	0.0	0.0	...	0.0	9.0	267162.0	644836.0	2.0	0.0	0.0	0.0	NaN	-1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
49994	266.0	0.0	0.0	792.0	990.0	18.0	432.0	336.56	0.0	2214786.0	...	0.0	0.0	26159.0	3640968.0	104.0	138432.0	0.0	0.0	NaN	-1
49995	357.0	0.0	0.0	132.0	165.0	2.0	0.0	288.08	0.0	6042420.0	...	0.0	9.0	604800.0	10367040.0	22.0	0.0	0.0	0.0	NaN	-1
49996	1078.0	0.0	2736.0	380.0	475.0	2.0	88.0	166.56	0.0	0.0	...	0.0	9.0	85120.0	1344900.0	150.0	9540.0	0.0	0.0	396.0	-1
49997	2807.0	7.0	1460.0	568.0	710.0	4.0	328.0	166.56	0.0	42210.0	...	0.0	27.0	4410.0	1242044.0	124.0	61734.0	0.0	0.0	NaN	-1
49999	1694.0	7.0	828.0	192.0	240.0	0.0	48.0	220.08	5.0	2691228.0	...	0.0	18.0	0.0	10679800.0	50.0	165270.0	0.0	0.0	NaN	1

44991 rows × 43 columns

Ahora pasaremos a un modelo de regresion lineal, con el objetivom uno de poder predecir cuales son las variables que mas afectan la compra de un nuevo paquete. Para eso, tenemos que hacer primero un Factor de Inflacion de Varianza. Lo cual nos permitira saber cuales son los valores de numerical data que son independientes y no multicolineales. Esto es, saber los valores que realmente nos aportan informacion y que a parte no nos digan lo mismo que otras variables en el data frame. Que no sean redundantes.

In [771…
```python
#VIF
from patsy import dmatrices
from statsmodels.stats.outliers_influence import variance_inflation_factor

features = "+".join(numerical_data_clean.columns.drop("Target"))
y, X = dmatrices('Target ~' + features, numerical_data_clean, return_type='dataframe')
```

In [772…
```python
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif["features"] = X.columns
```

```
/Users/diegotoledano/opt/anaconda3/lib/python3.8/site-packages/statsmodels/stats/outliers_influence.py:193: RuntimeWarning: divide by zero encountered in double_scalars
  vif = 1. / (1. - r_squared_i)
```

In [773…
```python
vif["VIF Factor"]
```

Out[773…
```
0     28.111154
1      2.381601
2      2.695191
3      1.435265
4           inf
5           inf
6      4.223529
7           inf
8      1.135592
9           inf
10    13.499510
11          inf
12     1.003485
13     2.481849
14     2.328489
15     2.341341
16     1.143563
17     2.941236
18          inf
19     1.688825
20          inf
21          inf
22     1.110851
23     8.509481
24          inf
25     1.330827
26     3.258327
27          inf
28     1.036025
29     1.090050
30          inf
31     8.737674
32     4.056738
33     1.118861
34          inf
35     1.787269
36     1.259939
37    31.948030
38          inf
39     2.030401
40          inf
41          inf
42     1.056002
Name: VIF Factor, dtype: float64
```

Tenemos nuestras variables ya con VIF implementado y pasamos a limpiar las que no tuvieron varianza, es decir no son independientes y las que tuvieron demasiada.

In [774…
```python
vif_clean = vif.loc[~np.isinf(vif.loc[:,"VIF Factor"]) & (vif.loc[:,"VIF Factor"]< 13)]

original_list = list(vif_clean['features'])
elements_to_remove = ["Var72","Var94","Var126","Var189"]
filtered = [i for i in original_list if i not in elements_to_remove ]
filtered
regression_list = filtered
vif_clean
```

Out[774…

	VIF Factor	features
1	2.381601	Var6
2	2.695191	Var7
3	1.435265	Var13
6	4.223529	Var24
8	1.135592	Var28
12	1.003485	Var57
13	2.481849	Var65
14	2.328489	Var72
15	2.341341	Var73
16	1.143563	Var74
17	2.941236	Var76
19	1.688825	Var81
22	1.110851	Var94
23	8.509481	Var109
25	1.330827	Var113
26	3.258327	Var119
28	1.036025	Var125
29	1.090050	Var126
31	8.737674	Var133
32	4.056738	Var134
33	1.118861	Var140
35	1.787269	Var144
36	1.259939	Var149
39	2.030401	Var163
42	1.056002	Var189

Ahora aplicaremos un modelo de Linear Regression. Preparamos los inputs y el array de objetivos. Y escalamos, esto es para que los inputs esten en la escala en la que estan los resultados con los que entrenara, y haya una relacion dimensional que nos pueda dar a entender mejor su relacion. Tambien preparamos el array de train y test para el modelo. Tambien se remueven absolutamente todos los valores NaN, ya que el modelo no acepta de estos.

In [775…
```python
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
import statsmodels.api as sm

scaler = MinMaxScaler()
inputs = numerical_data_clean[regression_list].dropna(axis=0)
target = numerical_data_clean[regression_list+["Target"]].dropna(axis=0)
targets = target["Target"].map({-1:0,1:1})
scaler.fit(inputs)
```

Out[775…
```
MinMaxScaler()
```

In [784…
```python
inputs_scaled = scaler.transform(inputs)
df_inputs_scaled = pd.DataFrame(inputs_scaled)

df_inputs_scaled
```

Out[784…

	0	1	2	3	4	5	6	7	8	9	...	11	12	13	14	15	16	17	18	19	20
0	0.011582	0.05	0.000930	0.028340	0.044674	0.582403	0.000000	0.095238	0.000246	0.069799	...	0.013948	0.419491	0.011137	0.000132	0.080772	0.012054	0.000355	0.111111	0.023478	0.002647
1	0.003984	0.00	0.000000	0.004049	0.080453	0.772569	0.000000	0.055556	0.000000	0.148444	...	0.005365	0.391453	0.005569	0.000000	0.275580	0.062252	0.000000	0.111111	0.016436	0.016436
2	0.039739	0.05	0.004569	0.052632	0.054916	0.942807	0.000000	0.468254	0.003644	0.086587	...	0.041845	0.436494	0.030698	0.001098	0.231774	0.043403	0.001537	0.444444	0.018930	0.029965
3	0.007810	0.05	0.016253	0.008097	0.051073	0.650339	0.052632	0.277778	0.001576	0.040532	...	0.004292	0.413167	0.001999	0.002780	0.010037	0.011516	0.006253	0.111111	0.015776	0.000000
4	0.004994	0.05	0.015950	0.004049	0.051073	0.023744	0.000000	0.452381	0.001379	0.010802	...	0.004292	0.434407	0.007139	0.000356	0.042706	0.007617	0.000682	0.111111	0.000156	0.004228
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
42148	0.002019	0.00	0.000000	0.036437	0.077207	0.062534	0.000000	0.007937	0.000000	0.018400	...	0.031116	0.430566	0.009376	0.000000	0.080557	0.039733	0.000000	0.000000	0.001545	0.009537
42149	0.002709	0.00	0.000000	0.004049	0.067929	0.393976	0.105263	0.039683	0.000000	0.142857	...	0.004292	0.417614	0.004807	0.000000	0.297632	0.000000	0.000000	0.111111	0.035714	0.000000
42150	0.008181	0.00	0.013827	0.004049	0.044674	0.084966	0.105263	0.476190	0.002955	0.011592	...	0.001073	0.326076	0.013850	0.005493	0.095526	0.006914	0.000000	0.111111	0.005026	0.000657
42151	0.021304	0.05	0.007379	0.008097	0.044674	0.939144	0.000000	0.611111	0.000640	0.032736	...	0.015021	0.418801	0.016563	0.001326	0.048957	0.022943	0.001297	0.333333	0.000260	0.004253
42152	0.012857	0.05	0.004185	0.000000	0.054916	0.162089	0.000000	0.103175	0.000000	0.236219	...	0.005365	0.421451	0.006282	0.001894	0.493867	0.016691	0.006436	0.222222	0.000000	0.011386

42153 rows × 21 columns

In [785…
```python
x_train, x_test, y_train, y_test = train_test_split(inputs_scaled, targets, test_size = 0.2, random_state=123)
```

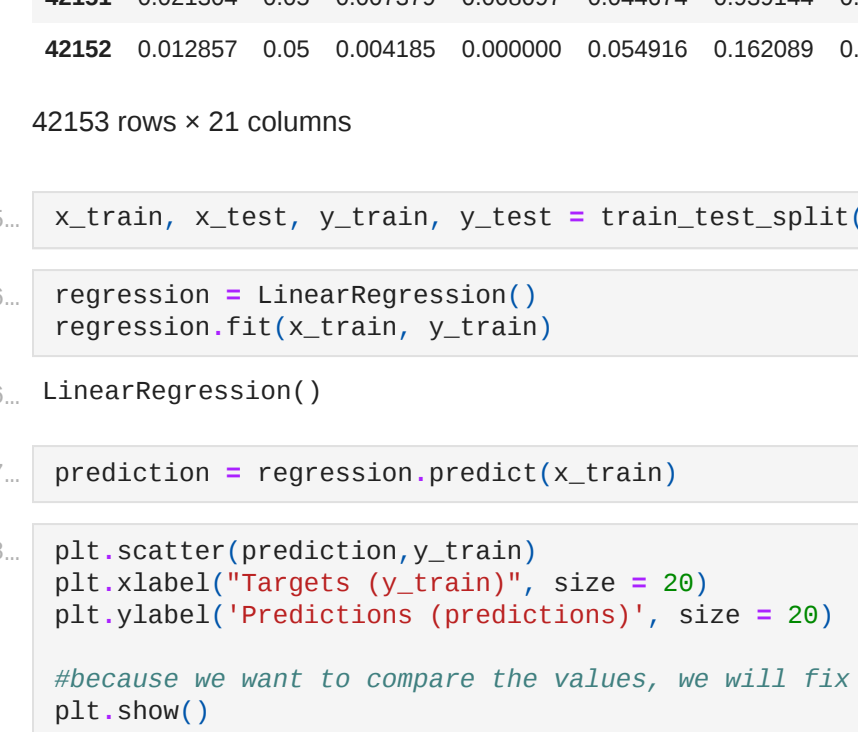
In [786…
```python
regression = LinearRegression()
regression.fit(x_train, y_train)
```

Out[786…
```
LinearRegression()
```

In [787…
```python
prediction = regression.predict(x_train)
```

In [788…
```python
plt.scatter(prediction,y_train)
plt.xlabel("Targets (y_train)", size = 20)
plt.ylabel('Predictions (predictions)', size = 20)

#because we want to compare the values, we will fix the limits
plt.show()
```



Podemos observar que en efecto hay valores de algunas variables que predicen una compra de paquete mas caro. Y que claramente, en general, entre mas esten por arriba de cero, se predice una compra. Esto es, estas variables suben, y tambien la probabilidad de compra.

In [789…
```python
regression.coef_
```

Out[789…
```
array([ 0.33805736,  0.01446217,  0.03048432,  0.28417328, -1.23094276,
        0.01040465,  0.02174942,  0.03541684, -0.08400338, -0.0127553 ,
       -0.17967084, -0.17656753,  0.37983261, -0.42600316,  0.11387957,
       -0.02771795, -0.05030008,  0.18675485, -0.06815024,  0.03944363,
       -0.01427571])
```

In [790…
```python
reg_summary = pd.DataFrame(inputs.columns.values, columns=["Features"])
reg_summary['Weights'] = regression.coef_
reg_summary
```

Out[790…

	Features	Weights
0	Var6	0.338057
1	Var7	0.014462
2	Var13	0.030484
3	Var24	0.284173
4	Var28	-1.230943
5	Var57	0.010405
6	Var65	0.021749
7	Var73	0.035417
8	Var74	-0.084003
9	Var76	-0.012755
10	Var81	-0.179671
11	Var109	-0.176568
12	Var113	0.379833
13	Var119	-0.426003
14	Var125	0.113880
15	Var133	-0.027718
16	Var134	-0.050300
17	Var140	0.186755
18	Var144	-0.068150
19	Var149	0.039444
20	Var163	-0.014276

""RESPUESTA PARA VALORES NUMERICOS""

En un analisis preliminar podemos ver que hay claramente variables con un peso considerable en lo positivo, que ya vimos predicen una compra. Var6, Var24, Var113, Var125 y Var 140, en el dataframe de valores numericos, son los que en cuanto a su presencia y su presencia mas alta daria la calificacion de 1 a 10. El siguiente paso sería desescalar estas variables y juzgar cuales serian las escalas en la vida real que darian esta calificacion.

En cuanto a los valores categoricos. No es posible hacer un VIF con ellos. Se tiene que hacer algo llamado GVIF. Lamentablemente aun no soy tan proficiente en analisis de datos como para poder hacer esto en el tiempo especificado. Sin duda soy capaz de hacerlo sin embargo. A continuacion explico el proceso que seguiría.

Primero se tendrían que trabajar los datos para pasarlos a ser numericos. Mi idea despues era limpiar por igual esta data, lo cual fue un problema por varias razones.

1. El metodo dummies dejaba muchos ceros, que no permitian un VIF bueno y mucho menos un modelo.
2. Como se puede observar debajo, el resultado es una matriz de 44991 filas × 6937 columnas.

No he tuve tiempo de atacar este problema exitosamente. Debajo esta una pequeña muestra del inicio de codigo de lo que menciono.

In [746…
```python
categorical_dummy = pd.concat([pd.get_dummies(categorical_data_3[col]) for col in categorical_data_3], axis=1, keys=categorical_data_3.columns)

categorical_dummy.shape
```

Out[746…
```
(44991, 69300)
```

En este dataframe se tiene la presencia de las variables categoricas de cada fila en manera numerica.

In [448…
```python
data_clean = df3.join(categorical_dummy)

data_clean
```

```
/Users/diegotoledano/opt/anaconda3/lib/python3.8/site-packages/pandas/core/reshape/merge.py:643: UserWarning: merging between different levels can give an unintended re
sult (1 levels on the left,2 on the right)
  warnings.warn(msg, UserWarning)
```

Out[448…

	Id	Var6	Var7	Var13	Var21	Var22	Var24	Var25	Var28	Var35	...	(Var228, iyHGyLCEkQ)	(Var228, n1OBWGkV3fbsHR75taC)	(Var228, r_7E)	(Var228, xwM2aC7IdeMC0)	(Var229, am7c)	(Var229, mj86)	(Var229, oJmt)	(Var229, sk2h)	(Target, -1)	(Target, 1)
0	1	1526.0	7.0	184.0	464.0	580.0	14.0	128.0	166.56	0.0	...	0	0	0	0	0	0	0	0	1	0
1	2	525.0	0.0	0.0	168.0	210.0	2.0	24.0	353.52	0.0	...	0	0	0	0	0	0	0	0	1	0
2	3	5236.0	7.0	904.0	1212.0	1515.0	26.0	816.0	220.08	0.0	...	0	0	0	0	1	0	0	0	1	0
3	4	NaN	0.0	0.0	NaN	0.0	NaN	0.0	22.08	0.0	...	0	0	0	0	0	0	0	0	1	0
4	5	1029.0	7.0	3216.0	64.0	80.0	4.0	64.0	200.00	0.0	...	0	0	0	0	0	1	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
49994	49995	266.0	0.0	0.0	792.0	990.0	18.0	432.0	336.56	0.0	...	0	0	0	0	0	0	0	0	1	0
49995	49996	357.0	0.0	0.0	132.0	165.0	2.0	0.0	288.08	0.0	...	0	0	0	0	0	0	0	0	1	0
49996	49997	1078.0	0.0	2736.0	380.0	475.0	2.0	88.0	166.56	0.0	...	0	0	0	0	1	0	0	0	1	0
49997	49998	2807.0	7.0	1460.0	568.0	710.0	4.0	328.0	166.56	0.0	...	0	0	0	0	0	0	0	0	1	0
49999	50000	1694.0	7.0	828.0	192.0	240.0	0.0	48.0	220.08	5.0	...	0	0	0	0	0	0	0	0	0	1

44991 rows × 69378 columns

'"CONCLUSIONES Y COMENTARIOS"'

En este ejercicio, creo haber abordado correctamente la visualización del problema. Así como la limpieza de data y su preparacion para un modelo predictivo. Se que hay errores desde ahorita y algunos que veo son los siguientes:

1. Un modelo de Regresión Logistica hubiera sido el indicado. Para la hora en la que me di cuanta de esto intente implementarlo con "statsmodels.api as sm". Sin embargo me encontre con unos problemas en cuanto a dimensiones de input y target que me tomarían mas tiempo.

2. La data categorica no fue modelada y no se llego a una predicción.

3. Con m as tiempo, pude haber desescalado los valores resultados del analisis a la parte de valores numericos. Y presentado un codigo de implementacion de calificación.

Actualmente estoy realizando estudios y tareas aparte del rubro de Data Analysis. No es excusa, lo menciono solo para dar a entender que mis habilidades actuales estan un poco oxidadas, que sigo aprendiendo y sobre todo, que pienso seguir aprendiendo, intensamente. Espero poder tener la oportunidad de presentar mi challenge y sobre todo, de poder colaborar en un futuro con Crabi.

Gracias.