Limpieza y análisis descriptivo de los datos

```
1 import numpy as np
 2 import pandas as pd
 3 import matplotlib.pyplot as plt
4 from sklearn.preprocessing import scale
 5 from sklearn import model_selection
 6 from sklearn.model_selection import RepeatedKFold
7 from sklearn.model_selection import train_test_split
8 from sklearn.decomposition import PCA
9 from sklearn.linear_model import LinearRegression
10 from sklearn.metrics import mean_squared_error
11 from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
12 from sklearn.model_selection import RepeatedStratifiedKFold
13 from sklearn.model_selection import cross_val_score
14 from IPython.display import HTML, display_html, display
1 # write here you code
 2 df = pd.read_excel('/content/diabetes_cortesia_promitat-1.xlsx')
 3 df.head()
```

	Unnamed: 0	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	altura	peso	IM
0	1	193	77	49	3.9	19	female	61	119	22.
1	2	146	79	41	3.6	19	female	60	135	26.
2	3	217	75	54	4.0	20	female	67	187	29.
3	4	226	97	70	3.2	20	female	64	114	19.
4										•

```
1 remove_cols = [col for col in df.columns if 'Unnamed' in col]
2 df.drop(remove_cols, axis='columns', inplace=True)
```

1 df

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_cin_cad	
0	193	77	49	3.9	19	61	119	22.5	118	70	32	38	0.84	1
1	146	79	41	3.6	19	60	135	26.4	108	58	33	40	0.83	1
2	217	75	54	4.0	20	67	187	29.3	110	72	40	45	0.89	1
3	226	97	70	3.2	20	64	114	19.6	122	64	31	39	0.79	1
4	164	91	67	2.4	20	70	141	20.2	122	86	32	39	0.82	1
•••														
385	227	105	44	5.2	83	59	125	25.2	150	90	35	40	0.88	1
386	226	279	52	4.3	84	60	192	37.5	144	88	41	48	0.85	
387	301	90	118	2.6	89	61	115	21.7	218	90	31	41	0.76	1
388	232	184	114	2.0	91	61	127	24.0	170	82	35	38	0.92	
389	165	94	69	2.4	92	62	217	39.7	160	82	51	51	1.00	1
390 ro	ws x 14 colum	ins												>

1 df.corr()

³ dfdibetesgen = df.copy()

⁴ df_regresion = df.copy()

⁵ df_discriminante = df.copy()

⁶ df = df.drop(['genero'], axis = 1)

⁷ df_con_diabetes = df.copy()

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura
colesterol	1.000000	0.158102	0.193162	0.475927	0.247333	-0.063601	0.062359	0.091695	0.207741	0.166241	0.134038
glucosa	0.158102	1.000000	-0.158302	0.282210	0.294392	0.098052	0.190358	0.129286	0.162777	0.020262	0.222336
hdl_chol	0.193162	-0.158302	1.000000	-0.681867	0.028210	-0.087238	-0.291883	-0.241860	0.031807	0.078342	-0.276697
prop_col_hdl	0.475927	0.282210	-0.681867	1.000000	0.163201	0.081162	0.278812	0.228407	0.115505	0.038242	0.313262
edad	0.247333	0.294392	0.028210	0.163201	1.000000	-0.082229	-0.056784	-0.009164	0.453417	0.068649	0.150585
altura	-0.063601	0.098052	-0.087238	0.081162	-0.082229	1.000000	0.255389	-0.259589	-0.040704	0.043617	0.057447
peso	0.062359	0.190358	-0.291883	0.278812	-0.056784	0.255389	1.000000	0.860147	0.097497	0.166477	0.847766
IMC	0.091695	0.129286	-0.241860	0.228407	-0.009164	-0.259589	0.860147	1.000000	0.121408	0.145304	0.810701
ps_sistolica	0.207741	0.162777	0.031807	0.115505	0.453417	-0.040704	0.097497	0.121408	1.000000	0.603662	0.210934
ps_diastolica	0.166241	0.020262	0.078342	0.038242	0.068649	0.043617	0.166477	0.145304	0.603662	1.000000	0.165846
cintura	0.134038	0.222336	-0.276697	0.313262	0.150585	0.057447	0.847766	0.810701	0.210934	0.165846	1.000000
caderas	0.093364	0.138223	-0.223837	0.208902	0.004675	-0.095906	0.826985	0.881728	0.155321	0.143898	0.835177
prop_cin_cad	0.091847	0.185117	-0.158777	0.243329	0.275188	0.252548	0.250461	0.100873	0.137871	0.077918	0.514177 •

1 df = df.drop(['diabetes'], axis = 1)
2 df.head()

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_cin_cad
0	193	77	49	3.9	19	61	119	22.5	118	70	32	38	0.84
1	146	79	41	3.6	19	60	135	26.4	108	58	33	40	0.83
2	217	75	54	4.0	20	67	187	29.3	110	72	40	45	0.89
3	226	97	70	3.2	20	64	114	19.6	122	64	31	39	0.79
4	164	91	67	2.4	20	70	141	20.2	122	86	32	39	0.82

1 df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 390 entries, 0 to 389 Data columns (total 13 columns): # Column Non-Null Count Dtype 0 colesterol 390 non-null int64 390 non-null glucosa int64 hdl_chol 390 non-null int64 prop_col_hdl 390 non-null float64 edad 390 non-null int64 altura 390 non-null int64 390 non-null 6 int64 peso IMC 390 non-null float64 8 ps_sistolica 390 non-null int64 ps_diastolica 390 non-null int64 10 cintura 390 non-null int64 390 non-null 11 caderas int64 12 prop_cin_cad 390 non-null dtypes: float64(3), int64(10) memory usage: 39.7 KB float64

1 df.isna().sum()

colesterol glucosa 0 hdl_chol prop_col_hdl 0 edad 0 altura peso 0 IMC ps_sistolica 0 ps_diastolica 0 cintura 0 0 caderas

```
prop_cin_cad 0
dtype: int64
```

1 df.shape

(390, 13)

1 df.describe()

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	ci
count	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390.00
mean	207.230769	107.338462	50.266667	4.524615	46.774359	65.951282	177.407692	28.775641	137.133333	83.289744	37.80
std	44.666005	53.798188	17.279069	1.736634	16.435911	3.918867	40.407824	6.600915	22.859528	13.498192	5.70
min	78.000000	48.000000	12.000000	1.500000	19.000000	52.000000	99.000000	15.200000	90.000000	48.000000	26.00
25%	179.000000	81.000000	38.000000	3.200000	34.000000	63.000000	150.250000	24.100000	122.000000	75.000000	33.00
50%	203.000000	90.000000	46.000000	4.200000	44.500000	66.000000	173.000000	27.800000	136.000000	82.000000	37.00
75%	229.000000	107.750000	59.000000	5.400000	60.000000	69.000000	200.000000	32.275000	148.000000	90.000000	41.00
max	443.000000	385.000000	120.000000	19.300000	92.000000	76.000000	325.000000	55.800000	250.000000	124.000000	56.00

Varianzas

0 colesterol 1995.052007 glucosa 2894.245046 hdl_chol 298.566238 3.015896 prop_col_hdl 270.139187 edad altura 15.357518 1632.792229 peso IMC 43.572079 522.558012 ps_sistolica 182.201180 ps_diastolica 33.188511 cintura 32.084774 caderas prop_cin_cad 0.005360

¹ varianza = df.var()

² display(HTML('<h1 style = "color:#FF85C0";> Varianzas</h1>'))

³ display_html(pd.DataFrame(varianza).style.set_table_styles([{'selector': 'th:not(.index_name)', 'props': 'background-color: #FF85C0; color

¹ cv = df.std() / df.mean() * 100

² display(HTML('<h1 style = "color:#C0FF85";> Coeficientes de variación</h1>'))

³ display_html(pd.DataFrame(cv).style.set_table_styles([{'selector': 'th:not(.index_name)', 'props': 'background-color: #C0FF85; color: whit

Coeficientes de variación

colesterol 21.553752 glucosa 50.120141 hdl_chol 34.374806 prop_col_hdl 38.381906 edad 35.138721 altura 5.942063

Matriz de varianzas y covarianzas S

				3	4	5	6	7	8	9	10	
0 1989	9.936489	378.937278	148.697436	36.822268	181.108481	-11.104142	112.259763	26.965621	211.569231	99.971598	34.401972	
1 378	8.937278	2886.823905	-146.777436	26.298592	259.640473	20.619053	412.751755	45.794142	199.670256	14.676292	68.731440	
2 148	8.697436	-146.777436	297.800684	-20.408615	7.990940	-5.892137	-203.272821	-27.515299	12.531111	18.225299	-27.472821	-
3 36	6.822268	26.298592	-20.408615	3.008163	4.646323	0.550943	19.515093	2.611600	4.573641	0.894150	3.126039	
4 181	1.108481	259.640473	7.990940	4.646323	269.446522	-5.282788	-37.615700	-0.991650	169.919829	15.191019	14.221775	
5 -11	1.104142	20.619053	-5.892137	0.550943	-5.282788	15.318139	40.337811	-6.697853	-3.637094	2.301295	1.293629	
6 112	2.259763	412.751755	-203.272821	19.515093	-37.615700	40.337811	1628.605582	228.837623	89.827692	90.569053	196.843057	1
7 26	6.965621	45.794142	-27.515299	2.611600	-0.991650	-6.697853	228.837623	43.460355	18.272735	12.913468	30.749892	
8 211	1.569231	199.670256	12.531111	4.573641	169.919829	-3.637094	89.827692	18.272735	521.218120	185.789573	27.707179	
9 99	9.971598	14.676292	18.225299	0.894150	15.191019	2.301295	90.569053	12.913468	185.789573	181.733997	12.863531	
10 34	4.401972	68.731440	-27.472821	3.126039	14.221775	1.293629	196.843057	30.749892	27.707179	12.863531	33.103412	
11 23	3.560750	42.012860	-21.851795	2.049677	0.434162	-2.123452	188.798008	32.883146	20.060000	10.974024	27.183609	
12 (0.299578	0.727249	-0.200344	0.030858	0.330287	0.072273	0.739051	0.048623	0.230149	0.076804	0.216309	>

^{1 #} Matriz de correlación R

^{1 #} pd.DataFrame(np.cov(df.T, bias = True)).style.set_table_styles([{'selector': 'th:not(.index_name)', 'props': 'background-color: #FF85FD;
2 display(HTML('<h1 style = "color:#FF85FD";> Matriz de varianzas y covarianzas S</h1>'))

³ display_html(pd.DataFrame(np.cov(df.T, bias = True)).style.set_table_styles([{'selector': 'th:not(.index_name)', 'props': 'background-colo

 $^{2 \; {\}tt display(HTML('<h1 \; style = "color:\#FFC485";> Matriz \; de \; correlación \; R</h1>'))}$

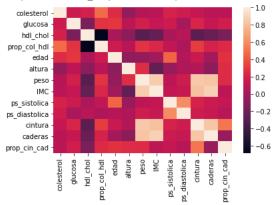
³ display_html(df.corr(method = 'pearson').style.set_table_styles([{'selector': 'th:not(.index_name)', 'props': 'background-color: #FFC485;

Matriz de correlación R

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diast
colesterol	1.000000	0.158102	0.193162	0.475927	0.247333	-0.063601	0.062359	0.091695	0.207741	0.
glucosa	0.158102	1.000000	-0.158302	0.282210	0.294392	0.098052	0.190358	0.129286	0.162777	0.0
hdl_chol	0.193162	-0.158302	1.000000	-0.681867	0.028210	-0.087238	-0.291883	-0.241860	0.031807	0.0
prop_col_hdl	0.475927	0.282210	-0.681867	1.000000	0.163201	0.081162	0.278812	0.228407	0.115505	0.0

```
1 import matplotlib.pyplot as plt
2 import seaborn as sns
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f659e27f090>

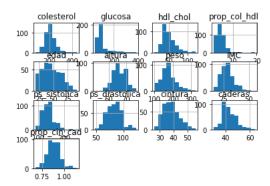


```
1 # Heatmap matriz de correlaciones
2 # ------
3 fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(12, 10))
4 corr_matrix = df_regresion.corr(method='pearson')
5 sns.heatmap(
6
      corr_matrix,
7
      annot
              = True,
8
              = False,
      cbar
9
      annot_kws = {"size": 8},
10
      vmin
              = -1.
11
      vmax
              = 1,
              = 0,
12
      center
              = sns.diverging_palette(20, 220, n=200),
13
      cmap
14
      square
              = True,
15
              = ax
      ax
16)
17
18 ax.set_xticklabels(
19
      ax.get_xticklabels(),
20
      rotation = 45,
21
      horizontalalignment = 'right',
22 )
24 ax.tick_params(labelsize = 10)
```

³ sns.heatmap(df_regresion.corr())



1 df_regresion.drop(['diabetes'], axis = 1).hist()
2 plt.show()



→ Estandarización de los datos

```
1 from sklearn import preprocessing
2 z_scaler = preprocessing.StandardScaler()
3 df_stan = pd.DataFrame(z_scaler.fit_transform(df))
4 df_stan = df_stan.set_axis(['colesterol', 'glucosa', 'hdl_chol', 'prop_col_hdl', 'edad', 'altura','peso','IMC','ps_sistolica','ps_diastoli
5
6 df_stan.head()
```

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas
0	-0.319013	-0.564655	-0.073401	-0.360132	-1.692029	-1.265070	-1.447312	-0.951944	-0.838071	-0.985822	-1.020105	-0.882489
1	-1.372619	-0.527432	-0.536983	-0.533102	-1.692029	-1.520574	-1.050840	-0.360358	-1.276087	-1.875972	-0.846299	-0.528950
2	0.218998	-0.601879	0.216339	-0.302476	-1.631108	0.267951	0.237692	0.079539	-1.188484	-0.837464	0.370339	0.354899
3	0.420753	-0.192418	1.143504	-0.763729	-1.631108	-0.498560	-1.571209	-1.391841	-0.662865	-1.430897	-1.193910	-0.705719
4	-0.969111	-0.304089	0.969660	-1.224982	-1.631108	1.034462	-0.902163	-1.300828	-0.662865	0.201045	-1.020105	-0.705719

Componentes principales

Observar y quitar outliers

```
1 from scipy.stats import chi2
2 from matplotlib import patches
```

 $^{{\}tt 3}$ import matplotlib.pyplot as plt

^{4 #} Import dataset and clean it

⁵ df1 = df_stan.to_numpy()

```
1 # Covariance matrix
 2 covariance = np.cov(df1 , rowvar=False)
 4 # Covariance matrix power of -1
 5 covariance_pm1 = np.linalg.matrix_power(covariance, -1)
 7 # Center point
 8 centerpoint = np.mean(df1 , axis=0)
1 # Distances between center point and
 2 distances = []
 3 for i, val in enumerate(df1):
        p1 = val
        p2 = centerpoint
        distance = (p1-p2).T.dot(covariance_pm1).dot(p1-p2)
 6
 7
        distances.append(distance)
 8 distances = np.array(distances)
10 # Cutoff (threshold) value from Chi-Sqaure Distribution for detecting outliers
11 cutoff = chi2.ppf(0.95, df1.shape[1])
12
13 # Index of outliers
14 outlierIndexes = np.where(distances > cutoff )
16 print('--- Index of Outliers ----')
17 print(outlierIndexes)
19 print('--- Observations found as outlier -----')
20 print(df1[ distances > cutoff , :])
     --- Index of Outliers ----
     (array([ 10, 82, 85, 89, 116, 139, 144, 153, 162, 167, 181, 184, 231,
            233, 234, 239, 242, 256, 261, 272, 276, 281, 296, 303, 306, 308,
            310, 316, 317, 341, 346, 347, 353, 354, 365, 371, 374, 386, 387,
           388, 389]),)
     --- Observations found as outlier ----
     [[-7.44939129e-01 -4.35231264e-02 3.86705165e+00 -1.74389146e+00
       -1.63110827e+00 1.03446193e+00 2.37692316e-01 -2.99682511e-01
      -2.24848354e-01 2.01044544e-01 -1.51077124e-01 -3.52179786e-01
       2.54592637e-011
      [-3.63847584e-01 8.87070037e-01 4.48129862e-01 -7.06072027e-01
       -9.60982389e-01 -1.00956671e+00 1.47666589e+00 2.20318181e+00
       1.25564665e-01 2.75223703e-01 2.62981154e+00 2.29936687e+00
       9.38415837e-01]
      [-7.00104829e-01 -3.22701076e-01 -9.42617985e-01 3.89404045e-01
       -9.00061854e-01 -7.54063133e-01 1.84835797e+00 2.40037718e+00
      -1.62650043e+00 -8.37463695e-01 1.23936721e+00 2.65290642e+00
      -1.38658304e+00]
      [-1.26053357e+00 -4.15760392e-01 -1.31348408e-01 -8.21385297e-01
       -8.39141319e-01 7.78958354e-01 3.23600837e+00 2.53689705e+00
      -1.18848416e+00 4.97761183e-01 2.45600600e+00 2.65290642e+00
       2.54592637e-01]
      1.25564665e-01 2.01044544e-01 2.28220046e+00 1.06197843e+00
       2.16929760e+00]
      [-9.48417872e-02 3.56717835e+00 -4.21087543e-01 1.01120868e-01
       -5.34538643e-01 7.78958354e-01 2.74041894e+00 2.08183081e+00
      -4.96418445e-02 -2.14929361e-02 1.76078383e+00 2.12259709e+00
      -1.55701282e-01]
      [-1.23811642e+00 -8.07468530e-02 -1.05851364e+00 1.58777503e-01
       -4.12697573e-01 -3.56460253e+00 2.37692316e-01 3.00713217e+00
       4.75977685e-01 -9.56720959e-02 2.27284170e-02 1.06197843e+00
      -1.38658304e+001
      [-6.10436230e-01 -4.34372255e-01 1.08555596e+00 -1.10966847e+00
       -4.12697573e-01 5.23454773e-01 2.14571163e+00 1.71777782e+00
       2.13167920e-01 1.09119446e+00 8.91756124e-01 1.94582731e+00
       -1.11305376e+001
      [-6.32853380e-01 -5.08819708e-01 2.41835598e+00 -1.51326492e+00
       -3.51777038e-01 1.54546910e+00 -1.47209122e+00 -1.93792098e+00
       3.00771175e-01 2.12970270e+00 -1.71532700e+00 -1.23602867e+00
      -1.38658304e+00]
      [-8.34607728e-01 -2.49112632e-02 -4.79035370e-01 -3.02475579e-01
       -3.51777038e-01 -1.26507030e+00 -1.67032699e+00 -1.20981499e+00
      \hbox{-1.49509555e+00} \hskip 3pt \hbox{-1.43089697e+00} \hskip 3pt \hbox{-1.54152146e+00} \hskip 3pt \hbox{-2.29664733e+00}
       1.21194512e+00]
      [ 2.57279903e+00 -3.78536665e-01 2.41835598e+00 -5.90758756e-01
       -2.29935968e-01 -2.54258820e+00 -1.42253228e+00 -2.84513637e-01
      -7.50467884e-01 1.09119446e+00 -1.02010483e+00 -3.52179786e-01
       -1.38658304e+00]
```

```
[-3.41430434e-01 3.09243267e-02 -3.63139716e-01 -7.18490379e-02 -2.29935968e-01 -4.98559552e-01 3.65725939e+00 4.09929115e+00 1.69366293e-01 -3.18209576e-01 2.62981154e+00 3.35998553e+00 -4.29230562e-01]
[-7.44939129e-01 1.22208358e+00 -9.42617985e-01 3.31747410e-01 1.96507777e-01 1.03446193e+00 2.12093215e+00 1.35372483e+00 9.57795588e-01 1.16537362e+00 2.28220046e+00 3.71352508e+00 -1.11305376e+00]

1 df_stan.drop(outlierIndexes[0], inplace = True,)
2 df.drop(outlierIndexes[0], inplace = True)
3 dfdibetesgen.drop(outlierIndexes[0], inplace = True)
4 dfedf.reset_index(drop = True)
2 dfdibetesgen=dfdibetesgen.reset_index(drop = True)
3 dfdibetesgen
```

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_c:
0	193	77	49	3.9	19	female	61	119	22.5	118	70	32	38	
1	146	79	41	3.6	19	female	60	135	26.4	108	58	33	40	
2	217	75	54	4.0	20	female	67	187	29.3	110	72	40	45	
3	226	97	70	3.2	20	female	64	114	19.6	122	64	31	39	
4	164	91	67	2.4	20	female	70	141	20.2	122	86	32	39	
•••														
344	252	161	87	2.9	80	female	62	162	29.6	160	100	44	41	
345	271	121	40	6.8	81	female	64	158	27.1	146	76	36	43	
346	240	88	49	4.9	82	female	63	170	30.1	180	86	41	46	
347	255	112	34	7.5	82	male	66	163	26.3	179	89	37	43	
348	227	105	44	5.2	83	female	59	125	25.2	150	90	35	40	
349 ro	ws × 15 colum	ns												•

▼ Cálculo de componentes principales

```
1 matriz_covarianza = np.cov(df_stan.T, bias = True)
2 eigenValues, eigenVectors = np.linalg.eig(matriz_covarianza)
3
4 idx = eigenValues.argsort()[::-1]
5 eigenValues = eigenValues[idx]
6 eigenVectors = eigenVectors[:,idx]
7
8 display(HTML('<h1 style = "color:#C0FF85";> <FONT FACE="optima">Valores propios</FONT></h1>'))
9 print(eigenValues)
10 display(HTML('<h1 style = "color:#C0FF85";> <FONT FACE="optima">Vectores propios</FONT></h1>'))
11 display_html(pd.DataFrame(eigenVectors, columns = ['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8','PC9','PC10','PC11', 'PC12', 'PC
```

¹ df_stan=df_stan.reset_index(drop = True)

Valores propios

```
[3.39486988e+00 1.69165264e+00 1.34014395e+00 1.20211751e+00 8.50945336e-01 7.43667242e-01 6.32972210e-01 4.76211366e-01 2.37574308e-01 1.24356817e-01 2.86126749e-02 3.93616649e-03 1.31812987e-03]
```

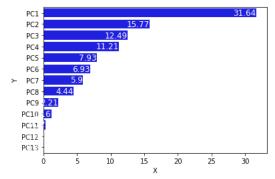
Vectores propios

```
PC<sub>2</sub>
                                                                                       PC3
                                                                                                           PC4
                                                                                                                                                   PC<sub>6</sub>
                                                                                                                                                                                            PC8
                                                                                                                                                                                                                PC9
                                                                                                                                                                                                                                   PC10
                                                                                                                                                                                                                                                       PC11
                                                                                                                                                                                                                                                                           PC12
                                          -0.130340 -0.254835 0.044639
                                                                                                       0.338896
                                                                                                                           0.219518 -0.744455 0.146938
                                                                                                                                                                                       0.008010
                                                                                                                                                                                                            0.089183
                                                                                                                                                                                                                                0.032947
                                                                                                                                                                                                                                                    0.410031
                                                                                                                                                                                                                                                                         0.001531
                colesterol
                 glucosa
                                          -0.159363 -0.184488 -0.142552
                                                                                                    0.148049
                                                                                                                           0.033842 0.096473 -0.452438
                                                                                                                                                                                       0.825956
                                                                                                                                                                                                           0.000524
                                                                                                                                                                                                                                0.001424
                                                                                                                                                                                                                                                   0.030630
                                                                                                                                                                                                                                                                         0.005572
                 hdl_chol
                                           0.201318 -0.083406
                                                                                 0.386347
                                                                                                    -0.151394
                                                                                                                           0.601240 -0.212420
                                                                                                                                                                 -0.050836
                                                                                                                                                                                       0.108626
                                                                                                                                                                                                           0.021570 -0.051396 -0.596720
                                                                                                                                                                                                                                                                       -0.009696
             prop_col_hdl
                                         -0.248051 -0.101966 -0.339894
                                                                                                     0.315274 -0.390304
                                                                                                                                             -0.268307
                                                                                                                                                                   0.135266 -0.038944 -0.024345
                                                                                                                                                                                                                              -0.038047
                                                                                                                                                                                                                                                  -0.683277
                                                                                                                                                                                                                                                                      -0.003274
                    edad
                                          -0.141802 -0.507275 -0.103662 0.281801
                                                                                                                           0.286366
                                                                                                                                               0.289543
                                                                                                                                                                 -0.325167 -0.432673
                                                                                                                                                                                                          -0.409883
                                                                                                                                                                                                                              -0.073358
                                                                                                                                                                                                                                                    0.010435
                    altura
                                           -0.030649 \quad -0.119991 \quad -0.366624 \quad -0.646766 \quad -0.049466 \quad -0.360297 \quad -0.405049 \quad -0.160279 \quad -0.005151 
                                                                                                                                                                                                                                0.042487
                                                                                                                                                                                                                                                    0.006865
                                                                                                                                                                                                                                                                       0.319200
  1 eigenVectors = pd.DataFrame(eigenVectors)
  2 eigenVectors2 = eigenVectors.drop([12, 11, 10], axis = 1)
                                          -0.400785 \quad 0.277453 \quad 0.185164 \quad 0.102431 \quad 0.091468 \quad 0.053623 \quad 0.048444 \quad 0.010608 \quad -0.052137 \quad -0.498423 \quad 0.048444 \quad 0.010608 \quad -0.052137 \quad -0.048423 \quad 0.048444 \quad 0.048419 \quad 0.04
  1 a = int(np.sum(eigenValues))
  2 b = eigenVectors2.shape[1]
  3 a == b
  1 eigenVectors = eigenVectors.to_numpy()
  2 np.linalg.norm(eigenVectors[:,0])
         1.0
  1 componentes_principales = eigenValues[0:7]
  2 componentes_principales
          array([3.39486988, 1.69165264, 1.34014395, 1.20211751, 0.85094534,
                        0.74366724, 0.63297221])
  1 \; print('\033[1m','\varianza de los primeros tres: ','\033[0m',"\{:.2f\}".format(sum(eigenValues[0:7]) / sum(eigenValues) * 100), '%')
            Varianza de los primeros tres: 91.87 %
  1 \; print('\033[1m','Primer \; eigenvalor: \; ','\033[0m',"{:.2f}".format((eigenValues[0] \; / \; sum(eigenValues)) \; * \; 100), \; '%')
   2 \; \texttt{print('\033[1m','Segundo eigenvalor: ','\033[0m',"\{:.2f\}''.format((eigenValues[1] \; / \; sum(eigenValues)) * 100), '%') }  
  3 print('\033[1m','Tercero eigenvalor: ','\033[0m',"\{:.2f\}".format((eigenValues[2] / sum(eigenValues)) * 100), '%')
  4 \; \text{print('\033[1m','Cuarto eigenvalor: ','\033[0m',"\{:.2f\}".format((eigenValues[3] \; / \; sum(eigenValues)) \; * \; 100), \; '%')}
  5 \; \text{print('\033[1m','Quinto eigenValues')}) \; * \; 100), \; '\$') \\
 6 print('\033[1m','Sexto eigenvalor: ','\033[0m',"{:.2f}".format((eigenValues[5] / sum(eigenValues)) * 100), '%')
7 print('\033[1m','Séptimo eigenvalor: ','\033[0m',"{:.2f}".format((eigenValues[6] / sum(eigenValues)) * 100), '%')
  8 print('\033[1m','Octavo eigenvalor: ','\033[0m',"{:.2f}".format((eigenValues[7] / sum(eigenValues)) * 100), '%')
  9 print('\033[1m','Noveno eigenvalor: ','\033[0m',"\{:.2f\}".format((eigenValues[8] / sum(eigenValues)) * 100), '%')
10 \; \texttt{print('\033[1m','becimo eigenvalues']','\033[0m',"{:..2f}".format((eigenValues[9] \; / \; sum(eigenValues)) \; * \; 100), \; '%')}
11 print('\033[1m','Onceavo eigenvalor: ','\033[0m',"\{:.2f\}".format((eigenValues[10] / sum(eigenValues)) * 100), '%') 12 print('\033[1m','Doceavo eigenvalor: ','\033[0m',"\{:.2f\}".format((eigenValues[11] / sum(eigenValues)) * 100), '%')
13 print('\033[1m','Treceavo eigenvalor: ','\033[0m',"{:.2f}".format((eigenValues[12] / sum(eigenValues)) * 100), '%')
            Primer eigenvalor:
                                                      31.64 %
            Segundo eigenvalor:
                                                      15.77 %
            Tercero eigenvalor:
                                                       12,49 %
            Cuarto eigenvalor:
                                                      11.21 %
            Quinto eigenvalor:
                                                      7.93 %
            Sexto eigenvalor:
                                                    6.93 %
           Séptimo eigenvalor:
                                                      5.90 %
            Octavo eigenvalor:
                                                      4.44 %
            Noveno eigenvalor:
                                                      2.21 %
           Décimo eigenvalor:
                                                      1.16 %
            Onceavo eigenvalor:
                                                        0.27 %
            Doceavo eigenvalor:
                                                        0.04 %
```

Treceavo eigenvalor:

0.01 %

```
1 labels=[]
 2 for i in range(len(eigenValues)):
 3 labels.append(round((eigenValues[i] / sum(eigenValues)) * 100,2))
 4 import seaborn as sns
 5 valgraf=[]
6 for i in range(len(eigenValues)):
 7 valgraf.append(eigenValues[i] / sum(eigenValues) * 100)
8 valgraf = pd.DataFrame(data
                                = valgraf)
9 valgraf.insert(1,"ss",['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8','PC9','PC10','PC11','PC12', 'PC13'],allow_duplicates=False)
10 valgraf=valgraf.rename({0:"X","ss":"Y"}, axis='columns')
11 sns.barplot(x = 'X', y = 'Y', data = valgraf, color = 'blue')
12
13 ax = plt.gca()
14 rects = ax.patches
15 for p,label in zip(ax.patches,labels):
      ax.text(p.get_width(), p.get_y() + p.get_height()/2., label,
16
17
               fontsize=12, color='white', ha='right', va='center')
18
```



```
1 print('\033[1m','Varianza acumulativa explicada: ','\033[0m',"{:.2f}".format(sum(eigenValues[0:12]) / sum(eigenValues) * 100), '%')
```

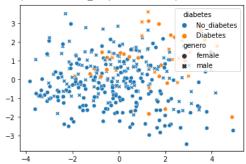
Varianza acumulativa explicada: 99.99 %

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_ci
0	193	77	49	3.9	19	female	61	119	22.5	118	70	32	38	
1	146	79	41	3.6	19	female	60	135	26.4	108	58	33	40	
2	217	75	54	4.0	20	female	67	187	29.3	110	72	40	45	
3	226	97	70	3.2	20	female	64	114	19.6	122	64	31	39	
4	164	91	67	2.4	20	female	70	141	20.2	122	86	32	39	

▼ Score plot

 $1 \; \text{sns.scatterplot(data=dfdibetesgen, x=T[:, 0], y=T[:, 1], style="genero", hue="diabetes", sizes=20) }$

<matplotlib.axes._subplots.AxesSubplot at 0x7f6599406390>



Loading plot

```
1 df_grafico = df_grafico.drop(['genero'], axis = 1)
2 df_grafico
```

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_cin_cad	
0	193	77	49	3.9	19	61	119	22.5	118	70	32	38	0.84	1
1	146	79	41	3.6	19	60	135	26.4	108	58	33	40	0.83	1
2	217	75	54	4.0	20	67	187	29.3	110	72	40	45	0.89	1
3	226	97	70	3.2	20	64	114	19.6	122	64	31	39	0.79	1
4	164	91	67	2.4	20	70	141	20.2	122	86	32	39	0.82	1
•••														
344	252	161	87	2.9	80	62	162	29.6	160	100	44	41	1.07	
345	271	121	40	6.8	81	64	158	27.1	146	76	36	43	0.84	1
346	240	88	49	4.9	82	63	170	30.1	180	86	41	46	0.89	1
347	255	112	34	7.5	82	66	163	26.3	179	89	37	43	0.86	1
348	227	105	44	5.2	83	59	125	25.2	150	90	35	40	0.88	1
349 ro	ws × 14 colum	ins												>

```
13
14 pca_step = pipeline.steps[1][1]
15 loadings = pd.DataFrame(
16
       pca_step.components_.T,
       columns=["PC1", "PC2"],
17
18
       index=df_grafico.drop(columns=["diabetes"]).columns,
19)
20
21
22 def loading plot(
23
       coeff, labels, scale=1, colors=None, visible=None, ax=plt, arrow_size=0.5
24):
25
       for i, label in enumerate(labels):
           if visible is None or visible[i]:
26
27
               ax.arrow(
28
                   0,
29
                   0,
30
                   coeff[i, 0] * scale,
                   coeff[i, 1] * scale,
31
                   head_width=arrow_size * scale,
32
33
                   head_length=arrow_size * scale,
                   color="#000" if colors is None else colors[i],
34
35
36
               ax.text(
37
                   coeff[i, 0] * 1.15 * scale,
                   coeff[i, 1] * 1.15 * scale,
38
39
40
                   color="#FB0000" if colors is None else colors[i],
                   ha="center",
41
42
                   va="center",
43
44
45
46 g = sns.scatterplot(data= pca_data, x= "PC1", y="PC2")
48 # Add loadings
49 loading_plot(loadings[["PC1", "PC2"]].values, loadings.index, scale=4, arrow_size=0.08)
50
51
52 # Add variance explained by the
53 g.set_xlabel(f"PC1 ({pca_step.explained_variance_ratio_[0]*100:.2f} %)")
54 g.set_ylabel(f"PC2 ({pca_step.explained_variance_ratio_[1]*100:.2f} %)")
56 plt.savefig("PCA_with_loadings.png", dpi=200)
57 plt.rcParams["figure.figsize"] = (12, 10)
58 plt.show()
         3
     PC2 (15.20 %)
        -3
```

→ PCR (Principal Components Regression)

PC1 (32.47 %)

1 df_con_diabetes

-4

-2

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_cin_cad	
0	193	77	49	3.9	19	61	119	22.5	118	70	32	38	0.84	1
1	146	79	41	3.6	19	60	135	26.4	108	58	33	40	0.83	1
2	217	75	54	4.0	20	67	187	29.3	110	72	40	45	0.89	1
3	226	97	70	3.2	20	64	114	19.6	122	64	31	39	0.79	1
4	164	91	67	2.4	20	70	141	20.2	122	86	32	39	0.82	1
385	227	105	44	5.2	83	59	125	25.2	150	90	35	40	0.88	1
386	226	279	52	4.3	84	60	192	37.5	144	88	41	48	0.85	
387	301	90	118	2.6	89	61	115	21.7	218	90	31	41	0.76	1

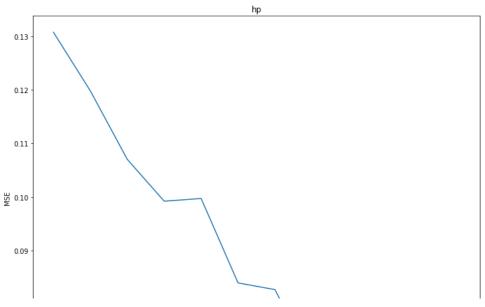
```
1 import numpy as np
 2 import pandas as pd
 3 import matplotlib.pyplot as plt
 4 from sklearn.preprocessing import scale
 5 from sklearn import model_selection
6 from sklearn.model selection import RepeatedKFold
7 from sklearn.model_selection import train_test_split
 8 from sklearn.decomposition import PCA
9 from sklearn.linear_model import LinearRegression
10 from sklearn.metrics import mean_squared_error
11
12 #select subset of data
13 col = "diabetes"
14 for i in range(df_con_diabetes.shape[0]):
if df_con_diabetes[col][i] == "No_diabetes":
     df_con_diabetes[col][i] = 0
16
17
    elif df_con_diabetes[col][i] == "Diabetes":
18
      df_con_diabetes[col][i] = 1
19
20 data = df_con_diabetes
21
22 #define predictor and response variables
23 X = data.iloc[:,0:12]
24 Y = data.iloc[:,13]
25
26 #scale predictor variables
27 pca = PCA()
28 X_reduced = pca.fit_transform(scale(X))
29
30 #define cross validation method
31 cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=42)
32
33 regr = LinearRegression()
34 \text{ mse} = []
35
36 # Calculate MSE with only the intercept
37 score = -1*model_selection.cross_val_score(regr, np.ones((len(X_reduced),1)), Y, cv=cv, scoring='neg_mean_squared_error').mean()
38 mse.append(score)
40 \# Calculate MSE using cross-validation, adding one component at a time
41 for i in np.arange(1, 12):
      score = -1*model_selection.cross_val_score(regr, X_reduced[:,:i], Y, cv=cv, scoring='neg_mean_squared_error').mean()
42
43
      mse.append(score)
44
45 # Plot cross-validation results
46 plt.plot(mse)
47 plt.xlabel('Number of Principal Components')
48 plt.ylabel('MSE')
49 plt.title('hp')
```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:16: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc app.launch_new_instance()

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:18: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc Text(0.5, 1.0, 'hp')



```
1 #calculate percentage of variation explained
```

2 np.cumsum(np.round(pca.explained_variance_ratio_, decimals=4)*100)

```
array([ 33.15, 49.52, 63.03, 73.03, 81.29, 89.34, 94.76, 97.06, 98.31, 99.4, 99.96, 100.01])
```

```
1 #split the dataset into training (70%) and testing (30%) sets
2 X_train,X_test,y_train,y_test = train_test_split(X,Y,test_size=0.3,random_state=0)
3
4 #scale the training and testing data
5 X_reduced_train = pca.fit_transform(scale(X_train))
6 X_reduced_test = pca.transform(scale(X_test))[:,:5]
7
8 #train PCR model on training data
9 regr = LinearRegression()
10 regr.fit(X_reduced_train[:,:5], y_train)
11
12 #calculate RMSE
13 pred = regr.predict(X_reduced_test)
14 print('\033[1m','MSE: ','\033[0m',np.sqrt(mean_squared_error(y_test, pred)))
MSE: 0.3033478080454169
```

- 1 Pruebar=pd.DataFrame(y_test)
- 2 Pruebar["Prediccion"]=pred
- 3 Pruebar

```
diabetes Prediccion
     54
                     -0.053377
     124
                 0
                      -0.023556
     349
                 0
                      0.180013
1 Pruebar.loc[Pruebar['Prediccion'] > 0.3, 'Prediccion'] = 1
2 Pruebar.loc[Pruebar['Prediccion'] < 0.3, 'Prediccion'] = 0</pre>
1 frecp=Pruebar['Prediccion'].value_counts()
2 frecp
    0.0
           92
          25
    1.0
    Name: Prediccion, dtype: int64
1 frecr=Pruebar['diabetes'].value_counts()
    0
        22
    Name: diabetes, dtype: int64
1 print("Accuracy :",frecp[0]/(frecr[0]+frecr[1]))
    Accuracy : 0.7863247863247863
```

→ Regresión lineal

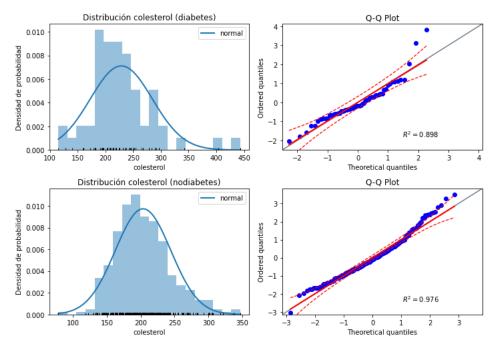
1 df_regresion

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_c:
0	193	77	49	3.9	19	female	61	119	22.5	118	70	32	38	
1	146	79	41	3.6	19	female	60	135	26.4	108	58	33	40	
2	217	75	54	4.0	20	female	67	187	29.3	110	72	40	45	
3	226	97	70	3.2	20	female	64	114	19.6	122	64	31	39	
4	164	91	67	2.4	20	female	70	141	20.2	122	86	32	39	
385	227	105	44	5.2	83	female	59	125	25.2	150	90	35	40	
386	226	279	52	4.3	84	female	60	192	37.5	144	88	41	48	
387	301	90	118	2.6	89	female	61	115	21.7	218	90	31	41	
388	232	184	114	2.0	91	female	61	127	24.0	170	82	35	38	
389	165	94	69	2.4	92	female	62	217	39.7	160	82	51	51	
390 ro	ws x 15 colum	ns												>

```
1 df_regresion.loc[df_regresion.diabetes == 'Diabetes', 'diabetes'] = 1
2 df_regresion.loc[df_regresion.diabetes == 'No_diabetes', 'diabetes'] = 0
1 df_regresion.loc[df_regresion.genero == 'female', 'genero'] = 0
2 df_regresion.loc[df_regresion.genero == 'male', 'genero'] = 1
1 !pip uninstall scipy -y
2 !pip uninstall pingouin -y
3 !pip install pingouin
```

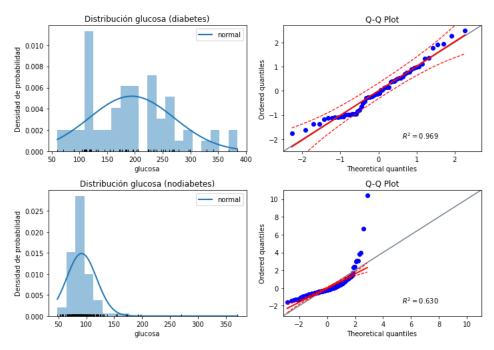
```
Found existing installation: scipy 1.7.3
    Uninstalling scipy-1.7.3:
       Successfully uninstalled scipy-1.7.3
             Skipping pingouin as it is not installed.
    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Collecting pingouin
       Downloading pingouin-0.5.2.tar.gz (185 kB)
                                         185 kB 5.1 MB/s
     Requirement already satisfied: numpy>=1.19 in /usr/local/lib/python3.7/dist-packages (from pingouin) (1.21.6)
    Collecting scipv>=1.7
       Downloading scipy-1.7.3-cp37-cp37m-manylinux_2_12_x86_64.manylinux2010_x86_64.whl (38.1 MB)
                                         | 38.1 MB 1.3 MB/s
     Requirement already satisfied: pandas>=1.0 in /usr/local/lib/python3.7/dist-packages (from pingouin) (1.3.5)
     Requirement already satisfied: matplotlib>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from pingouin) (3.2.2)
     Requirement already satisfied: seaborn>=0.11 in /usr/local/lib/python3.7/dist-packages (from pingouin) (0.11.2)
     Collecting statsmodels>=0.13
       Downloading statsmodels-0.13.2-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (9.8 MB)
                   9.8 MB 38.4 MB/s
     Requirement already satisfied: scikit-learn<1.1.0 in /usr/local/lib/python3.7/dist-packages (from pingouin) (1.0.2)
     Collecting pandas flavor>=0.2.0
       Downloading pandas_flavor-0.3.0-py3-none-any.whl (6.3 kB)
     Collecting outdated
       Downloading outdated-0.2.1-py3-none-any.whl (7.5 kB)
     Requirement already satisfied: tabulate in /usr/local/lib/python3.7/dist-packages (from pingouin) (0.8.10)
     Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.2->pingouin) (0.11.0)
     Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.2->pingouin) (1.4.4)
     Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.2-ypingouin) (2.8
     Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=3
     Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->matplotlib>=3.0.2
     Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas>=1.0->pingouin) (2022.2.1)
    Collecting pandas_flavor>=0.2.0
       Downloading pandas_flavor-0.2.0-py2.py3-none-any.whl (6.6 kB)
     Requirement already satisfied: xarray in /usr/local/lib/python3.7/dist-packages (from pandas_flavor>=0.2.0->pingouin) (0.20.2)
     Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1->matplotlib>=3.0.2->ping
     Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn<1.1.0->pingouin) (3.
     Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn<1.1.0->pingouin) (1.1.0)
     Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.7/dist-packages (from statsmodels>=0.13->pingouin) (0.5.2)
     Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.7/dist-packages (from statsmodels>=0.13->pingouin) (21.3)
     Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from outdated->pingouin) (2.23.0)
    Collecting littleutils
       Downloading littleutils-0.2.2.tar.gz (6.6 kB)
     Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests->outdated->pingouin) (2.10)
     Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests->outdated->pingouin) (3.0.4
     Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests->outdated->pingouin) (2022
     Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages (from requests->outd
     Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.7/dist-packages (from xarray->pandas_flavor>=0.2.0->pingo
     Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (from importlib-metadata->xarray->pandas_flavor>=0
     Building wheels for collected packages: pingouin, littleutils
       Building wheel for pingouin (setup.py) ... done
       Created wheel for pingouin: filename=pingouin-0.5.2-py3-none-any.whl size=196206 sha256=10e3ebf627281f573d1071be58133f7783ceb4b0d1d
       Stored in directory: /root/.cache/pip/wheels/11/5a/63/a6d32fc26fa462c731f65480bfb98ff7bd39b8ebcb4bc6c2fe
       Building wheel for littleutils (setup.py) \dots done
       Created wheel for littleutils: filename=littleutils-0.2.2-py3-none-any.whl size=7048 sha256=fe5438283bb92b23678fce47d3fd84143fb8681
       Stored in directory: /root/.cache/pip/wheels/d6/64/cd/32819b511a488e4993f2fab909a95330289c3f4e0f6ef4676d
 1 from scipy import stats
 2 import pingouin as pg
 1 df regresion.groupby('diabetes').size()
    diabetes
    0
         330
    1
          60
     dtype: int64
 1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 colesterol_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'colesterol']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(colesterol_diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(colesterol_diabetes), max(colesterol_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=colesterol_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 axs[0, 0].plot(colesterol_diabetes, np.full_like(colesterol_diabetes, -0.01), '|k', markeredgewidth=1)
```

```
17 axs[0, 0].set_title('Distribución colesterol (diabetes)')
18 axs[0, 0].set_xlabel('colesterol')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(colesterol diabetes, dist='norm', ax=axs[0, 1])
25 colesterol_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'colesterol']
26 mu, sigma = stats.norm.fit(colesterol nodiabetes)
27 x_hat = np.linspace(min(colesterol_nodiabetes), max(colesterol_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=colesterol_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(colesterol_nodiabetes, np.full_like(colesterol_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución colesterol (nodiabetes)')
33 axs[1, 0].set_xlabel('colesterol')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
37 pg.qqplot(colesterol_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```



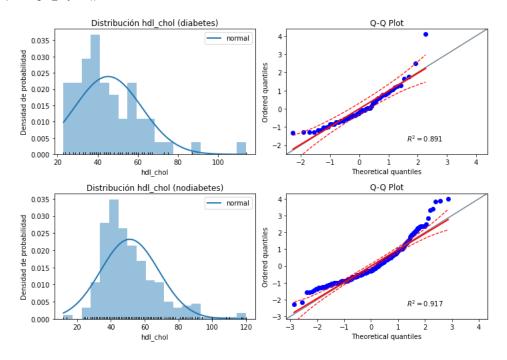
```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 glucosa_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'glucosa']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(glucosa_diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(glucosa_diabetes), max(glucosa_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=glucosa_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 axs[0, 0].plot(glucosa_diabetes, np.full_like(glucosa_diabetes, -0.01), '|k', markeredgewidth=1)
17 axs[0, 0].set_title('Distribución glucosa (diabetes)')
18 axs[0, 0].set_xlabel('glucosa')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(glucosa_diabetes, dist='norm', ax=axs[0, 1])
24
25 glucosa_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'glucosa']
26 mu, sigma = stats.norm.fit(glucosa_nodiabetes)
```

```
27 x_hat = np.linspace(min(glucosa_nodiabetes), max(glucosa_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=glucosa_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(glucosa_nodiabetes, np.full_like(glucosa_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución glucosa (nodiabetes)')
33 axs[1, 0].set_xlabel('glucosa')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
36
37 pg.qqplot(glucosa_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```

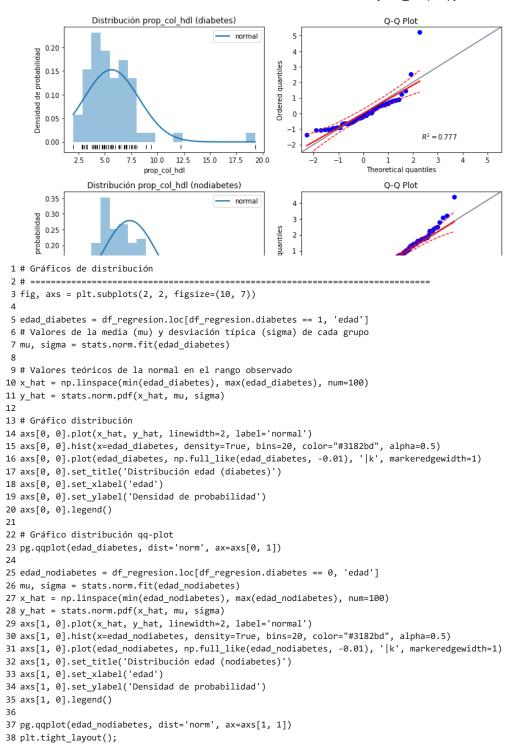


```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 hdl_chol_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'hdl_chol']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(hdl_chol_diabetes)
 8
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(hdl_chol_diabetes), max(hdl_chol_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=hdl_chol_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 axs[0, 0].plot(hdl chol diabetes, np.full like(hdl chol diabetes, -0.01), '|k', markeredgewidth=1)
17 axs[0, 0].set_title('Distribución hdl_chol (diabetes)')
18 axs[0, 0].set_xlabel('hdl_chol')
19 axs[0, 0].set ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(hdl_chol_diabetes, dist='norm', ax=axs[0, 1])
24
25 hdl_chol_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'hdl_chol']
26 mu, sigma = stats.norm.fit(hdl_chol_nodiabetes)
27 x_hat = np.linspace(min(hdl_chol_nodiabetes), max(hdl_chol_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=hdl_chol_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(hdl_chol_nodiabetes, np.full_like(hdl_chol_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución hdl_chol (nodiabetes)')
33 axs[1, 0].set_xlabel('hdl_chol')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
```

```
37 pg.qqplot(hdl_chol_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```

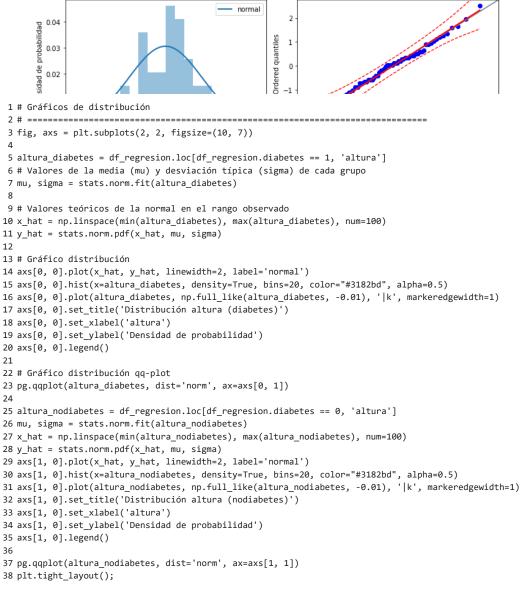


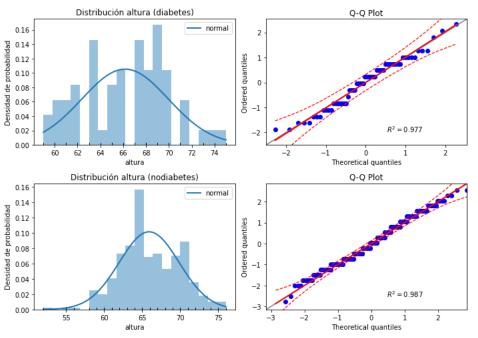
```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 prop_col_hdl_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'prop_col_hdl']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(prop_col_hdl_diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(prop_col_hdl_diabetes), max(prop_col_hdl_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=prop_col_hdl_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 axs[0, 0].plot(prop_col_hdl_diabetes, np.full_like(prop_col_hdl_diabetes, -0.01), '|k', markeredgewidth=1)
17 axs[0, 0].set_title('Distribución prop_col_hdl (diabetes)')
18 axs[0, 0].set_xlabel('prop_col_hdl')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(prop_col_hdl_diabetes, dist='norm', ax=axs[0, 1])
24
25 prop_col_hdl_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'prop_col_hdl']
26 mu, sigma = stats.norm.fit(prop col hdl nodiabetes)
27 x_hat = np.linspace(min(prop_col_hdl_nodiabetes), max(prop_col_hdl_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=prop_col_hdl_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(prop_col_hdl_nodiabetes, np.full_like(prop_col_hdl_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución prop_col_hdl (nodiabetes)')
33 axs[1, 0].set_xlabel('prop_col_hdl')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
37 pg.qqplot(prop_col_hdl_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```



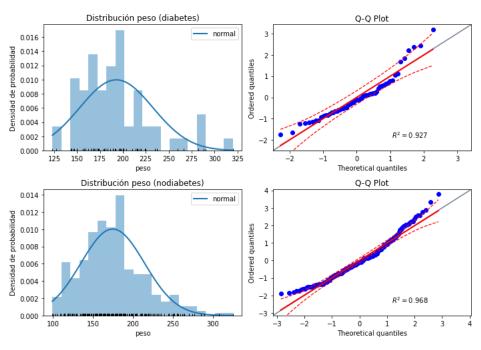
Q-Q Plot

Distribución edad (diabetes)

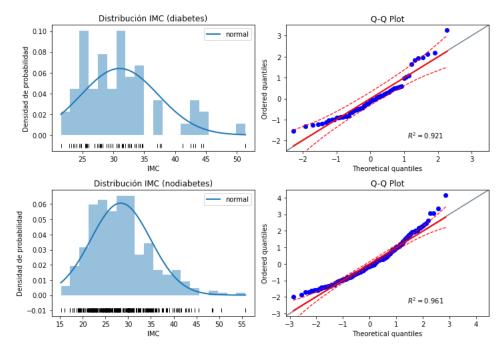




```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 peso_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'peso']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(peso diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x hat = np.linspace(min(peso diabetes), max(peso diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=peso_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 \ axs[0,\ 0]. plot(peso\_diabetes, \ np.full\_like(peso\_diabetes, \ -0.01), \ '|k', \ markeredgewidth=1)
17 axs[0, 0].set_title('Distribución peso (diabetes)')
18 axs[0, 0].set_xlabel('peso')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(peso_diabetes, dist='norm', ax=axs[0, 1])
25 peso nodiabetes = df regresion.loc[df regresion.diabetes == 0, 'peso']
26 mu, sigma = stats.norm.fit(peso_nodiabetes)
27 x_hat = np.linspace(min(peso_nodiabetes), max(peso_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=peso_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(peso_nodiabetes, np.full_like(peso_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución peso (nodiabetes)')
33 axs[1, 0].set_xlabel('peso')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
36
37 pg.qqplot(peso nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```

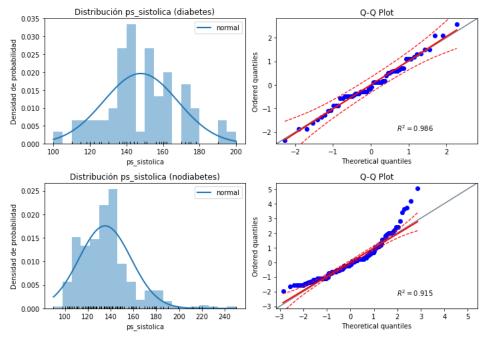


```
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=IMC_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16~axs[0,~0].plot(IMC\_diabetes,~np.full\_like(IMC\_diabetes,~-0.01),~'|k',~markeredgewidth=1)
17 axs[0, 0].set_title('Distribución IMC (diabetes)')
18 axs[0, 0].set_xlabel('IMC')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(IMC_diabetes, dist='norm', ax=axs[0, 1])
25 IMC_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'IMC']
26 mu, sigma = stats.norm.fit(IMC_nodiabetes)
27 x_hat = np.linspace(min(IMC_nodiabetes), max(IMC_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=IMC_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(IMC_nodiabetes, np.full_like(IMC_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución IMC (nodiabetes)')
33 axs[1, 0].set_xlabel('IMC')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
36
37 pg.qqplot(IMC_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```



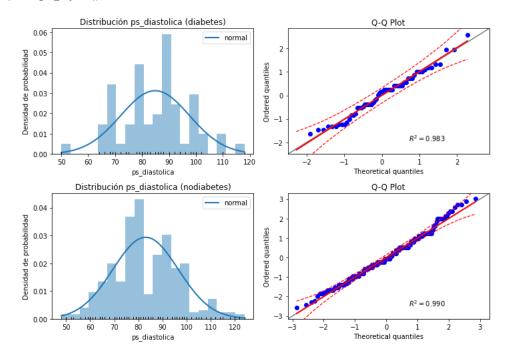
```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 ps_sistolica_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'ps_sistolica']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(ps_sistolica_diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(ps_sistolica_diabetes), max(ps_sistolica_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=ps_sistolica_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16~axs[0,~0]. plot(ps\_sistolica\_diabetes,~np.full\_like(ps\_sistolica\_diabetes,~-0.01),~'|k',~markeredgewidth=1)
17 axs[0, 0].set_title('Distribución ps_sistolica (diabetes)')
18 axs[0, 0].set xlabel('ps sistolica')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
```

```
21
22 # Gráfico distribución ga-plot
23 pg.qqplot(ps_sistolica_diabetes, dist='norm', ax=axs[0, 1])
25 ps_sistolica_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'ps_sistolica']
26 mu, sigma = stats.norm.fit(ps_sistolica_nodiabetes)
27 x_hat = np.linspace(min(ps_sistolica_nodiabetes), max(ps_sistolica_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=ps sistolica nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(ps_sistolica_nodiabetes, np.full_like(ps_sistolica_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución ps_sistolica (nodiabetes)')
33 axs[1, 0].set_xlabel('ps_sistolica')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
36
37 pg.qqplot(ps_sistolica_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```

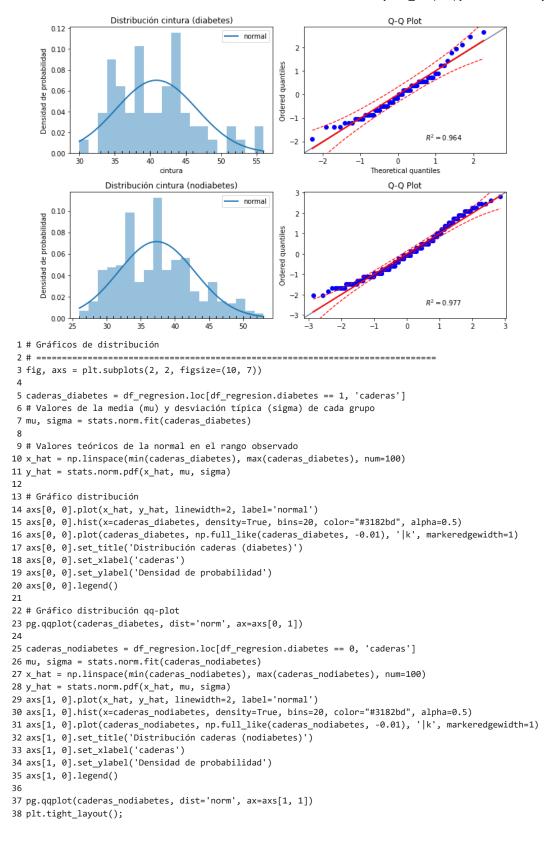


```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 ps_diastolica_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'ps_diastolica']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(ps_diastolica_diabetes)
 9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(ps_diastolica_diabetes), max(ps_diastolica_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15~axs[0,~0].hist(x=ps\_diastolica\_diabetes,~density=True,~bins=20,~color="\#3182bd",~alpha=0.5)
16 axs[0, 0].plot(ps_diastolica_diabetes, np.full_like(ps_diastolica_diabetes, -0.01), '|k', markeredgewidth=1)
17 axs[0, 0].set_title('Distribución ps_diastolica (diabetes)')
18 axs[0, 0].set_xlabel('ps_diastolica')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
22 # Gráfico distribución qq-plot
23 pg.qqplot(ps_diastolica_diabetes, dist='norm', ax=axs[0, 1])
25 ps_diastolica_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'ps_diastolica']
26 mu, sigma = stats.norm.fit(ps_diastolica_nodiabetes)
27 x_hat = np.linspace(min(ps_diastolica_nodiabetes), max(ps_diastolica_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=ps_diastolica_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
```

```
31 axs[1, 0].plot(ps_diastolica_nodiabetes, np.full_like(ps_diastolica_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución ps_diastolica (nodiabetes)')
33 axs[1, 0].set_xlabel('ps_diastolica')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
36
37 pg.qqplot(ps_diastolica_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```



```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 cintura_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'cintura']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(cintura_diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(cintura_diabetes), max(cintura_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=cintura_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 axs[0, 0].plot(cintura_diabetes, np.full_like(cintura_diabetes, -0.01), '|k', markeredgewidth=1)
17 axs[0, 0].set_title('Distribución cintura (diabetes)')
18 axs[0, 0].set_xlabel('cintura')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
22 # Gráfico distribución qq-plot
23 pg.qqplot(cintura diabetes, dist='norm', ax=axs[0, 1])
25 cintura_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'cintura']
26 mu, sigma = stats.norm.fit(cintura_nodiabetes)
27 x_hat = np.linspace(min(cintura_nodiabetes), max(cintura_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=cintura_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(cintura_nodiabetes, np.full_like(cintura_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución cintura (nodiabetes)')
33 axs[1, 0].set_xlabel('cintura')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
37 pg.qqplot(cintura_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```



```
Distribución caderas (diabetes)
                                                                                                        Q-Q Plot
  0.14
                                                            normal
  0.12
  0.10
                                                                       Ordered quantiles
                                                                            1
  0.08
e
  0.06
                                                                            0
  0.04
  0.02
                                                                                                                   R^2 = 0.929
  0.00
                                                                                                   Theoretical quantiles
                  Distribución caderas (nodiabetes)
                                                                                                        Q-Q Plot
```

```
1 # Gráficos de distribución
 3 fig, axs = plt.subplots(2, 2, figsize=(10, 7))
 5 prop_cin_cad_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'prop_cin_cad']
 6 # Valores de la media (mu) y desviación típica (sigma) de cada grupo
 7 mu, sigma = stats.norm.fit(prop_cin_cad_diabetes)
9 # Valores teóricos de la normal en el rango observado
10 x_hat = np.linspace(min(prop_cin_cad_diabetes), max(prop_cin_cad_diabetes), num=100)
11 y_hat = stats.norm.pdf(x_hat, mu, sigma)
12
13 # Gráfico distribución
14 axs[0, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
15 axs[0, 0].hist(x=prop_cin_cad_diabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
16 axs[0, 0].plot(prop_cin_cad_diabetes, np.full_like(prop_cin_cad_diabetes, -0.01), '|k', markeredgewidth=1)
17 axs[0, 0].set_title('Distribución prop_cin_cad (diabetes)')
18 axs[0, 0].set_xlabel('prop_cin_cad')
19 axs[0, 0].set_ylabel('Densidad de probabilidad')
20 axs[0, 0].legend()
21
22 # Gráfico distribución qq-plot
23 pg.qqplot(prop_cin_cad_diabetes, dist='norm', ax=axs[0, 1])
24
25 prop_cin_cad_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'prop_cin_cad']
26 mu, sigma = stats.norm.fit(prop_cin_cad_nodiabetes)
27 x_hat = np.linspace(min(prop_cin_cad_nodiabetes), max(prop_cin_cad_nodiabetes), num=100)
28 y_hat = stats.norm.pdf(x_hat, mu, sigma)
29 axs[1, 0].plot(x_hat, y_hat, linewidth=2, label='normal')
30 axs[1, 0].hist(x=prop_cin_cad_nodiabetes, density=True, bins=20, color="#3182bd", alpha=0.5)
31 axs[1, 0].plot(prop_cin_cad_nodiabetes, np.full_like(prop_cin_cad_nodiabetes, -0.01), '|k', markeredgewidth=1)
32 axs[1, 0].set_title('Distribución prop_cin_cad (nodiabetes)')
33 axs[1, 0].set_xlabel('prop_cin_cad')
34 axs[1, 0].set_ylabel('Densidad de probabilidad')
35 axs[1, 0].legend()
36
37 pg.qqplot(prop_cin_cad_nodiabetes, dist='norm', ax=axs[1, 1])
38 plt.tight_layout();
```

```
Distribución prop_cin_cad (diabetes)
                                                                       Q-Q Plot
1 pg.normality(data = df_regresion, dv = 'colesterol', group = 'diabetes')
                    pval normal
    0 0.977382 0.000047
                           False
    1 0.909198 0.000290
                           False
1 pg.normality(data = df_regresion, dv = 'colesterol', group = 'diabetes')
                    pval normal
    0 0.977382 0.000047
                           False
    1 0.909198 0.000290
                           False
                                               | ē _1 ]
    ₽ 2 I
                 /
1 pg.normality(data = df_regresion, dv = 'hdl_chol', group = 'diabetes')
                       pval normal
    0 0.918263 1.999520e-12
                               False
    1 0.898020 1.114847e-04
                              False
1 pg.normality(data = df_regresion, dv = 'prop_col_hdl', group = 'diabetes')
              W
                        pval normal
    0 0.953534 1.038987e-08
                               False
    1 0.794430 9.833369e-08
                               False
1 pg.normality(data = df_regresion, dv = 'edad', group = 'diabetes')
              W
                       pval normal
    0 0.964710 3.585699e-07
                               False
    1 0.988666 8.517852e-01
                               True
1 pg.normality(data = df_regresion, dv = 'altura', group = 'diabetes')
                    pval normal
    0 0.987116 0.004932
    1 0.972026 0.183158
                            True
1 pg.normality(data = df_regresion, dv = 'peso', group = 'diabetes')
                    pval normal
    0 0.967653 0.000001
                            False
    1 0.929339 0.001862
                           False
1 pg.normality(data = df_regresion, dv = 'IMC', group = 'diabetes')
                        pval normal
    0 0.961125 1.081305e-07
                               False
    1 0.921511 8.826908e-04
                               False
1 pg.normality(data = df_regresion, dv = 'ps_sistolica', group = 'diabetes')
```

```
pval normal
    0 0.917309 1.647114e-12
                               False
    1 0007112 7705110<sub>--</sub>01
                               Truo
1 pg.normality(data = df_regresion, dv = 'ps_diastolica', group = 'diabetes')
                    pval normal
    0 0.989816 0.021375
                           False
    1 0.986149 0.729652
                            True
1 pg.normality(data = df_regresion, dv = 'cintura', group = 'diabetes')
                    pval normal
    0 0.975017 0.000017
                           False
    1 0 961822 0 057783
                            True
1 pg.normality(data = df_regresion, dv = 'caderas', group = 'diabetes')
                       pval normal
    0 0.959707 6.847286e-08
                               False
    1 0.928343 1.690424e-03
                               False
1 pg.normality(data = df_regresion, dv = 'prop_cin_cad', group = 'diabetes')
             W
                    pval normal
    0 0.990321 0.028313
                           False
    1 0.966866 0.102353
                            True
1 # Test para datos independientes (p-value, intervalos de confianza)
2 # ------
3 colesterol_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'colesterol']
4 colesterol_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'colesterol']
\label{eq:constraint} \texttt{6 pg.ttest} (\texttt{x=colesterol\_diabetes}, \ \texttt{y = colesterol\_nodiabetes}, \ \texttt{alternative='two-sided'}, \ \texttt{correction=False})
                 T dof alternative
                                       p-val
                                                    CI95% cohen-d
                                                                       BF10
                                                                               power
    T-test 4.110156 388
                           two-sided 0.000048 [13.17, 37.34] 0.576843 383.017 0.983823
1 # Test para datos independientes (p-value, intervalos de confianza)
2 # -----
3 glucosa_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'glucosa']
4 glucosa_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'glucosa']
6 pg.ttest(x=glucosa_diabetes, y=glucosa_nodiabetes, alternative='two-sided', correction=False)
                  T dof alternative
                                            p-val
                                                         CI95% cohen-d
                                                                             BF10 power
    T-test 18.729901 388
                            two-sided 3.205119e-56 [91.84, 113.39] 2.628665 2.72e+52
1 # Test para datos independientes (p-value, intervalos de confianza)
3 hdl chol diabetes = df regresion.loc[df regresion.diabetes == 1, 'hdl chol']
4 hdl_chol_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'hdl_chol']
6 pg.ttest(x=hdl_chol_diabetes, y=hdl_chol_nodiabetes, alternative='two-sided', correction=False)
                                                    CI95% cohen-d BF10
                 T dof alternative
                                        p-val
    T-test -2.444045 388
                            two-sided 0.014968 [-10.63, -1.15] 0.343012 2.479 0.68369
```

```
1 # Test para datos independientes (p-value, intervalos de confianza)
3 prop_col_hdl_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'prop_col_hdl']
4 prop_col_hdl_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'prop_col_hdl']
6 pg.ttest(x=prop_col_hdl_diabetes, y=prop_col_hdl_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                         p-val
                                                   CI95% cohen-d
    T-test 5.589515 388
                          two-sided 4.298115e-08 [0.85, 1.77] 0.784465 2.522e+05 0.99985
1 # Test para datos independientes (p-value, intervalos de confianza)
3 edad_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'edad']
4 edad_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'edad']
6 pg.ttest(x=edad_diabetes, y=edad_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                         p-val
                                                    CI95% cohen-d
                                                                       BF10 power
    T-test 6.239951 388
                          two-sided 1.146990e-09 [9.41, 18.07] 0.875751 7.643e+06
                                                                               1.0
1 # Test para datos independientes (p-value, intervalos de confianza)
3 altura_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'altura']
4 altura_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'altura']
6 pg.ttest(x=altura_diabetes, y=altura_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                      p-val
                                                CI95% cohen-d BF10
    T-test 0.462345 388
                          two-sided 0.644093 [-0.83, 1.34] 0.064888 0.169 0.074703
1 # Test para datos independientes (p-value, intervalos de confianza)
3 peso_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'peso']
4 peso_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'peso']
6 pg.ttest(x=peso_diabetes, y=peso_nodiabetes, alternative='two-sided', correction=False)
               T dof alternative
                                     n-val
                                                CT95% cohen-d
                                                                BF10
                                                                        power
    T-test 3.25399 388
                         two-sided 0.001238 [7.22, 29.25] 0.456684 21.063 0.900772
1 # Test para datos independientes (p-value, intervalos de confianza)
3 IMC = df_regresion.loc[df_regresion.diabetes == 1, 'IMC']
4 IMC_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'IMC']
6 pg.ttest(x=IMC_diabetes, y=IMC_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                      p-val
                                                CI95% cohen-d BF10
    T-test 2.892241 388
                          two-sided 0.004041 [0.85, 4.46] 0.405914 7.526 0.822546
1 # Test para datos independientes (p-value, intervalos de confianza)
3 ps_sistolica_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'ps_sistolica']
4 ps_sistolica_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'ps_sistolica']
6 pg.ttest(x=ps_sistolica_diabetes, y=ps_sistolica_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                                CI95% cohen-d
    T-test 3.991465 388
                          two-sided 0.000079 [6.38, 18.76] 0.560186 246.536 0.978391
1 # Test para datos independientes (p-value, intervalos de confianza)
3 ps_diastolica_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'ps_diastolica']
4 ps_diastolica_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'ps_diastolica']
```

```
6 pg.ttest(x=ps_diastolica_diabetes, y=ps_diastolica_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                     p-val
                                               CI95% cohen-d BF10
    T-test 0.973289 388
                         two-sided 0.331016 [-1.88, 5.57] 0.136597 0.238 0.163002
1 # Test para datos independientes (p-value, intervalos de confianza)
3 cintura_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'cintura']
4 cintura_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'cintura']
6 pg.ttest(x=cintura_diabetes, y=cintura_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                     p-val
                                               CI95% cohen-d
                                                                 BF10
                                                                         power
    T-test 4.514098 388
                          two-sided 0.000008 [2.01, 5.11] 0.633535 1878.979 0.994504
1 # Test para datos independientes (p-value, intervalos de confianza)
3 caderas_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'caderas']
4 caderas_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'caderas']
6 pg.ttest(x=caderas_diabetes, y=caderas_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                              CI95% cohen-d
    T-test 2.862119 388
                          two-sided 0.004436 [0.71, 3.8] 0.401687 6.944 0.814624
1 # Test para datos independientes (p-value, intervalos de confianza)
2 # -----
3 prop_cin_cad_diabetes = df_regresion.loc[df_regresion.diabetes == 1, 'prop_cin_cad']
4 prop_cin_cad_nodiabetes = df_regresion.loc[df_regresion.diabetes == 0, 'prop_cin_cad']
6 pg.ttest(x=prop_cin_cad_diabetes, y=prop_cin_cad_nodiabetes, alternative='two-sided', correction=False)
                T dof alternative
                                     p-val
                                               CI95% cohen-d
                                                               BF10
                                                                       power
    T-test 3.513984 388
                          two-sided 0.000494 [0.02, 0.06] 0.493173 47.454 0.938864
```

Regresión con variables significativas

1 df_regresion.head()

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_cin_
0	193	77	49	3.9	19	0	61	119	22.5	118	70	32	38	
1	146	79	41	3.6	19	0	60	135	26.4	108	58	33	40	
2	217	75	54	4.0	20	0	67	187	29.3	110	72	40	45	
3	226	97	70	3.2	20	0	64	114	19.6	122	64	31	39	
4	164	91	67	2.4	20	0	70	141	20.2	122	86	32	39	
- 4														>

```
1 df1 = df_regresion.drop(["altura"], axis = 1)
2 df2 = df1.drop(["ps_diastolica"], axis = 1)
3 df2
```

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	peso	IMC	ps_sistolica	cintura	caderas	prop_cin_cad	diabetes
0	193	77	49	3.9	19	0	119	22.5	118	32	38	0.84	0
1	146	79	41	3.6	19	0	135	26.4	108	33	40	0.83	0
2	217	75	54	4.0	20	0	187	29.3	110	40	45	0.89	0
3	226	97	70	3.2	20	0	114	19.6	122	31	39	0.79	0
4	164	91	67	2.4	20	0	141	20.2	122	32	39	0.82	0
385	227	105	44	5.2	83	0	125	25.2	150	35	40	0.88	0
1 df2 = d	f2.drop(["ge	nero"], a	axis = 1)										
J.,	JU 1	20	110	۷.۷	ر ن	U	110	41.7	210	v i	71	0.70	U

```
1 df3 = df2.drop(['colesterol'], axis=1)
2 df3 = df3.drop(['glucosa'], axis =1)
3 df3 = df3.drop(['hdl_chol'], axis =1)
4 df3 = df3.drop(['prop_col_hdl'], axis =1)
5 df3 = df3.drop(['edad'], axis =1)
6 df3 = df3.drop(['peso'], axis =1)
7 df3 = df3.drop(['IMC'], axis =1)
8 df3 = df3.drop(['IMC'], axis =1)
9 df3 = df3.drop(['cintura'], axis =1)
10 df3 = df3.drop(['caderas'], axis =1)
11 Y = df3.drop(['prop_cin_cad'], axis =1)
12
13 Y
```

	diabetes
0	0
1	0
2	0
3	0
4	0
385	0
386	1
387	0
388	1
389	0

390 rows × 1 columns

```
1 dfx = df2.drop(['diabetes'], axis=1)
2 dfx
```

colesterol glucosa hdl_chol prop_col_hdl edad peso IMC ps_sistolica cintura caderas prop_cin_cad 1 from numpy import * I 140 17 17 133 40.4 100 บ.บอ 1 Xn = ones(390)2 226 97 70 32 20 11*1* 10 6 122 21 30 N 79 1 dfx['Xn'] = Xn2 X = dfx3 X

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	peso	IMC	ps_sistolica	cintura	caderas	prop_cin_cad	Xn
0	193	77	49	3.9	19	119	22.5	118	32	38	0.84	1.0
1	146	79	41	3.6	19	135	26.4	108	33	40	0.83	1.0
2	217	75	54	4.0	20	187	29.3	110	40	45	0.89	1.0
3	226	97	70	3.2	20	114	19.6	122	31	39	0.79	1.0
4	164	91	67	2.4	20	141	20.2	122	32	39	0.82	1.0
•••												
385	227	105	44	5.2	83	125	25.2	150	35	40	0.88	1.0
386	226	279	52	4.3	84	192	37.5	144	41	48	0.85	1.0
387	301	90	118	2.6	89	115	21.7	218	31	41	0.76	1.0
388	232	184	114	2.0	91	127	24.0	170	35	38	0.92	1.0
389	165	94	69	2.4	92	217	39.7	160	51	51	1.00	1.0

390 rows × 12 columns

```
1 Xt = X.transpose()
```

2 Xt

	0	1	2	3	4	5	6	7	8	9	 380	
colesterol	193.00	146.00	217.00	226.00	164.00	170.00	149.00	164.00	230.00	179.00	 157.00	252
glucosa	77.00	79.00	75.00	97.00	91.00	69.00	77.00	71.00	112.00	105.00	 92.00	161
hdl_chol	49.00	41.00	54.00	70.00	67.00	64.00	49.00	63.00	64.00	60.00	 47.00	87
prop_col_hdl	3.90	3.60	4.00	3.20	2.40	2.70	3.00	2.60	3.60	3.00	 3.30	2
edad	19.00	19.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	 80.00	80
peso	119.00	135.00	187.00	114.00	141.00	161.00	115.00	145.00	159.00	170.00	 212.00	162
IMC	22.50	26.40	29.30	19.60	20.20	27.60	21.00	19.70	24.90	35.50	 29.60	29
ps_sistolica	118.00	108.00	110.00	122.00	122.00	108.00	105.00	108.00	100.00	140.00	 156.00	160
cintura	32.00	33.00	40.00	31.00	32.00	37.00	31.00	29.00	31.00	34.00	 47.00	44
caderas	38.00	40.00	45.00	39.00	39.00	40.00	37.00	36.00	39.00	46.00	 48.00	41
prop_cin_cad	0.84	0.83	0.89	0.79	0.82	0.93	0.84	0.81	0.79	0.74	 0.98	1
Xn	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	 1.00	1

12 rows × 390 columns

```
1 Xt = Xt.to_numpy()
2 Xt
    array([[193. , 146. , 217. , ..., 301. , 232. , 165.
           [ 77. , 79. , 75. , ..., 90. , 184. , 94. ],
           [ 49. , 41. , 54. , ..., 118. , 114. ,
           [ 38. , 40. , 45. , ..., 41. , 38. , 
[ 0.84, 0.83, 0.89, ..., 0.76, 0.92, 
[ 1. , 1. , 1. , ..., 1. , 1. ,
1 A = Xt@X
2 print(A)
    [[1.7524466e+07 8.8228800e+06 4.1205440e+06 3.8004010e+05 3.8509360e+06
      1.4381871e+07 2.3361639e+06 1.1165628e+07 3.0740080e+06 3.4838270e+06
      7.1350340e+04 8.0820000e+04]
     [8.8228800e+06 5.6192640e+06 2.0470200e+06 1.9966590e+05 2.0593280e+06
      7.5876140e + 06 \ 1.2224656e + 06 \ 5.8185470e + 06 \ 1.6120870e + 06 \ 1.8161290e + 06
      3.7180150e+04 4.1862000e+04]
     [4.1205440e+06 2.0470200e+06 1.1015700e+06 8.0741200e+04 9.2008100e+05
      3.3986240e+06 5.5338670e+05 2.6932490e+06 7.3167400e+05 8.3429900e+05
      1.7200530e+04 1.9604000e+04]
     [3.8004010e+05 1.9966590e+05 8.0741200e+04 9.1573200e+03 8.4350100e+04
      3.2066450e+05 5.1796020e+04 2.4376920e+05 6.8043200e+04 7.6663600e+04
      1.5673260e+03 1.7646000e+03]
     [3.8509360e+06 2.0593280e+06 9.2008100e+05 8.4350100e+04 9.5834200e+05
      3.2216010e+06 5.2453850e+05 2.5678550e+06 6.9635700e+05 7.8443500e+05
      1.6207030e+04 1.8242000e+04]
     [1.4381871e+07 7.5876140e+06 3.3986240e+06 3.2066450e+05 3.2216010e+06
      1.2909817e+07 2.0802045e+06 9.5231510e+06 2.6969030e+06 3.0482260e+06
      6.1270350e+04 6.9189000e+04]
     [2.3361639e+06 1.2224656e+06 5.5338670e+05 5.1796020e+04 5.2453850e+05
      2.0802045e+06 3.3988417e+05 1.5461052e+06 4.3697990e+05 4.9530560e+05
      9.9103020e+03 1.1222500e+041
     [1.1165628e+07 5.8185470e+06 2.6932490e+06 2.4376920e+05 2.5678550e+06
      9.5231510e+06 1.5461052e+06 7.5374400e+06 2.0361280e+06 2.3071380e+06
      4.7227970e+04 5.3482000e+04]
     [3.0740080e+06 1.6120870e+06 7.3167400e+05 6.8043200e+04 6.9635700e+05
      2.6969030e+06 4.3697990e+05 2.0361280e+06 5.7220100e+05 6.4555500e+05
      1.3101530e+04 1.4769000e+04]
     [3.4838270e+06 1.8161290e+06 8.3429900e+05 7.6663600e+04 7.8443500e+05
      3.0482260e+06 4.9530560e+05 2.3071380e+06 6.4555500e+05 7.3333300e+05
      1.4772100e+04 1.6767000e+04]
     [7.1350340e+04 3.7180150e+04 1.7200530e+04 1.5673260e+03 1.6207030e+04
      6.1270350e+04 9.9103020e+03 4.7227970e+04 1.3101530e+04 1.4772100e+04
      3.0505220e+02 3.4374000e+02]
     [8.0820000e+04 4.1862000e+04 1.9604000e+04 1.7646000e+03 1.8242000e+04
      6.9189000e+04 1.1222500e+04 5.3482000e+04 1.4769000e+04 1.6767000e+04
      3.4374000e+02 3.9000000e+02]]
1 A = pd.DataFrame(A)
```

2 A

	0	1	2	3	4	5	6	7	8	9	10	
0	17524466.00	8822880.00	4120544.00	380040.100	3850936.00	14381871.00	2336163.900	11165628.00	3074008.00	3483827.0	71350.3400	8
1	8822880.00	5619264.00	2047020.00	199665.900	2059328.00	7587614.00	1222465.600	5818547.00	1612087.00	1816129.0	37180.1500	4
2	4120544.00	2047020.00	1101570.00	80741.200	920081.00	3398624.00	553386.700	2693249.00	731674.00	834299.0	17200.5300	1
3	380040.10	199665.90	80741.20	9157.320	84350.10	320664.50	51796.020	243769.20	68043.20	76663.6	1567.3260	
4	3850936.00	2059328.00	920081.00	84350.100	958342.00	3221601.00	524538.500	2567855.00	696357.00	784435.0	16207.0300	1
5	14381871.00	7587614.00	3398624.00	320664.500	3221601.00	12909817.00	2080204.500	9523151.00	2696903.00	3048226.0	61270.3500	6
6	2336163.90	1222465.60	553386.70	51796.020	524538.50	2080204.50	339884.170	1546105.20	436979.90	495305.6	9910.3020	1
7	11165628.00	5818547.00	2693249.00	243769.200	2567855.00	9523151.00	1546105.200	7537440.00	2036128.00	2307138.0	47227.9700	5
8	3074008.00	1612087.00	731674.00	68043.200	696357.00	2696903.00	436979.900	2036128.00	572201.00	645555.0	13101.5300	1.
9	3483827.00	1816129.00	834299.00	76663.600	784435.00	3048226.00	495305.600	2307138.00	645555.00	733333.0	14772.1000	1
10	71350.34	37180.15	17200.53	1567.326	16207.03	61270.35	9910.302	47227.97	13101.53	14772.1	305.0522	
11	80820.00	41862.00	19604.00	1764.600	18242.00	69189.00	11222.500	53482.00	14769.00	16767.0	343.7400	•

```
1 A = A.to_numpy()
2 A
    array([[1.7524466e+07, 8.8228800e+06, 4.1205440e+06, 3.8004010e+05,
             3.8509360e+06, 1.4381871e+07, 2.3361639e+06, 1.1165628e+07,
            3.0740080e+06, 3.4838270e+06, 7.1350340e+04, 8.0820000e+04],
           [8.8228800e+06, 5.6192640e+06, 2.0470200e+06, 1.9966590e+05,
             2.0593280e+06, 7.5876140e+06, 1.2224656e+06, 5.8185470e+06,
            1.6120870e+06, 1.8161290e+06, 3.7180150e+04, 4.1862000e+04],
           [4.1205440e+06, 2.0470200e+06, 1.1015700e+06, 8.0741200e+04,
            9.2008100e+05, 3.3986240e+06, 5.5338670e+05, 2.6932490e+06,
            7.3167400e+05, 8.3429900e+05, 1.7200530e+04, 1.9604000e+04],
           [3.8004010e+05, 1.9966590e+05, 8.0741200e+04, 9.1573200e+03,
            8.4350100e+04, 3.2066450e+05, 5.1796020e+04, 2.4376920e+05,
            6.8043200e+04, 7.6663600e+04, 1.5673260e+03, 1.7646000e+03],
           [3.8509360e+06, 2.0593280e+06, 9.2008100e+05, 8.4350100e+04,
             9.5834200e+05, 3.2216010e+06, 5.2453850e+05, 2.5678550e+06,
            6.9635700e+05, 7.8443500e+05, 1.6207030e+04, 1.8242000e+04],
           [1.4381871e+07, 7.5876140e+06, 3.3986240e+06, 3.2066450e+05,
             3.2216010e+06, 1.2909817e+07, 2.0802045e+06, 9.5231510e+06,
           2.6969030e+06, 3.0482260e+06, 6.1270350e+04, 6.9189000e+04], [2.3361639e+06, 1.2224656e+06, 5.5338670e+05, 5.1796020e+04,
             5.2453850e+05, 2.0802045e+06, 3.3988417e+05, 1.5461052e+06,
            4.3697990e+05, 4.9530560e+05, 9.9103020e+03, 1.1222500e+04],
           [1.1165628e+07, 5.8185470e+06, 2.6932490e+06, 2.4376920e+05,
            2.5678550e+06, 9.5231510e+06, 1.5461052e+06, 7.5374400e+06,
            2.0361280e+06, 2.3071380e+06, 4.7227970e+04, 5.3482000e+04],
           [3.0740080e+06, 1.6120870e+06, 7.3167400e+05, 6.8043200e+04,
            6.9635700e+05, 2.6969030e+06, 4.3697990e+05, 2.0361280e+06,
            5.7220100e+05, 6.4555500e+05, 1.3101530e+04, 1.4769000e+04],
           [3.4838270e+06, 1.8161290e+06, 8.3429900e+05, 7.6663600e+04,
             7.8443500e+05, 3.0482260e+06, 4.9530560e+05, 2.3071380e+06,
            6.4555500e+05, 7.3333300e+05, 1.4772100e+04, 1.6767000e+04],
            [7.1350340e+04, 3.7180150e+04, 1.7200530e+04, 1.5673260e+03,
            1.6207030e+04, 6.1270350e+04, 9.9103020e+03, 4.7227970e+04,
            1.3101530e+04, 1.4772100e+04, 3.0505220e+02, 3.4374000e+02],
            [8.0820000e+04, 4.1862000e+04, 1.9604000e+04, 1.7646000e+03,
            1.8242000e+04, 6.9189000e+04, 1.1222500e+04, 5.3482000e+04,
            1.4769000e+04, 1.6767000e+04, 3.4374000e+02, 3.9000000e+02]])
1 Ainversa = np.linalg.inv(A)
2 Ainversa
    array([[ 4.94430189e-06, 8.30875813e-08, -1.22794199e-05,
             -1.43097618e-04, -4.06099610e-07, 6.18196040e-07,
            -2.98639638e-06, -2.41166045e-07, -9.33860049e-06,
           4.75920174e-06, 4.46317211e-04, 1.51663302e-05], [ 8.30875813e-08, 1.07553607e-06, -2.64098832e-07,
             -9.13663609e-06, -9.72883975e-07, -3.97380290e-07,
             1.37210804e-06, -1.02102650e-08, -6.73618227e-06,
             5.74597225e-06, 2.84163462e-04, -2.42524205e-04],
           [-1.22794199e-05, -2.64098832e-07, 4.77307218e-05, 4.71891155e-04, -9.05120278e-07, -9.70830515e-07,
             7.51892417e-06, -3.58922130e-07, -1.34130321e-05,
           2.16459407e-05, 5.31877151e-04, -2.80539720e-03],
[-1.43097618e-04, -9.13663609e-06, 4.71891155e-04,
             5.94388341e-03, -9.07028984e-06, -2.14736135e-05,
             8.45551974e-05, -2.06786682e-08, -2.50053847e-05,
             1.18466966e-04, -3.24524961e-03, -1.94616133e-02],
            [-4.06099610e-07, -9.72883975e-07, -9.05120278e-07,
            -9.07028984e-06, 1.50549218e-05, 3.00758329e-06, -2.49867666e-06, -3.81868142e-06, 4.27629967e-05,
            -4.91626514e-05, -2.85862572e-03, 2.64670074e-03],
            [ 6.18196040e-07, -3.97380290e-07, -9.70830515e-07,
             -2.14736135e-05, 3.00758329e-06, 9.17431337e-06,
            -2.37450137e-05, 8.55723245e-08, -3.23892292e-05,
            -1.44509578e-06, 1.71470938e-04, 1.01328182e-04],
           [-2.98639638e-06, 1.37210804e-06, 7.51892417e-06,
             8.45551974e-05, -2.49867666e-06, -2.37450137e-05,
             3.55405554e-04, 1.22756200e-06, 1.18669169e-05,
             -2.36407289e-04, -1.24301512e-03, 4.45500033e-03],
            [-2.41166045e-07, -1.02102650e-08, -3.58922130e-07,
             -2.06786682e-08, -3.81868142e-06, 8.55723245e-08,
             1.22756200e-06, 6.49603885e-06, -2.40363445e-05,
             1.50409740e-05, 9.51180903e-04, -1.26826832e-03],
            [-9.33860049e-06, -6.73618227e-06, -1.34130321e-05,
             -2.50053847e-05, 4.27629967e-05, -3.23892292e-05,
            1.18669169e-05, -2.40363445e-05, 1.83010783e-02, -1.57246877e-02, -7.82434502e-01, 6.82764846e-01],
           [ 4.75920174e-06, 5.74597225e-06, 2.16459407e-05,
             1.18466966e-04, -4.91626514e-05, -1.44509578e-06,
             -2.36407289e-04, 1.50409740e-05, -1.57246877e-02,
             1.40072738e-02, 6.80852183e-01, -6.02746866e-01],
```

```
[ 4.46317211e-04, 2.84163462e-04, 5.31877151e-04, -3.24524961e-03, -2.85862572e-03, 1.71470938e-04,
                -1.24301512e-03, 9.51180903e-04, -7.82434502e-01, 6.80852183e-01, 3.42189389e+01, -2.99276846e+01], [ 1.51663302e-05, -2.42524205e-04, -2.80539720e-03,
                 -1.94616133e-02, 2.64670074e-03, 1.01328182e-04, 4.45500033e-03, -1.26826832e-03, 6.82764846e-01, -6.02746866e-01, -2.99276846e+01, 2.65939799e+01]])
1 Nueva = Ainversa@Xt
2 Nueva
     array([[ 4.31608871e-05, -5.15180002e-05, 9.01256291e-05, ...,
                  -1.47743852e-04, -3.15022041e-04, -1.99519131e-04],
                [ 1.31352433e-05, 1.72443476e-05, -7.29809082e-06, ..., -3.76445694e-05, 6.24762729e-05, -5.71001596e-05],
                [-1.82277581e-04, -8.71463511e-05, -1.32723083e-04, ...,
                   1.10249133e-03, 1.43846040e-03, 4.68519758e-04],
                [-3.51138200e-03, \ 4.53538241e-04, \ 1.13212097e-03, \ \ldots,
                  -4.71751924e-05, 2.64130438e-03, -1.81948747e-02],
                [-1.77509031e-01, 2.42653868e-02, 4.51447764e-02, ...,
                -1.01895544e-01, 1.44400029e-01, -8.83122433e-01],
[1.82634158e-01, 1.79443486e-02, -3.60063082e-02, ...,
-2.94707724e-02, -2.01912801e-01, 7.26062396e-01]])
1 Y = Y.to_numpy()
2 Y
     array([[0],
                [0],
                [0],
                [0],
                [0],
                [0],
                [0],
                [0],
                [0],
                [0],
                [0],
                [0],
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                [0],
                [0],
                [0],
```

```
[0],
                                              [0],
                                              [0],
                                              [0],
                                              [a]
1 ab = Nueva@Y
2 ab
                 array([[0.00030509457219941887],
                                              [0.004264917984844847],
                                              [0.00031474161544478097],
                                              [0.01218605325178176],
                                              [0.0015301827209237991],
                                              [-0.0006872416282639533],
                                              [0.004503259029726481],
                                              [0.0005624032704808533],
                                              [0.037401686754168995],
                                              [-0.030643187273626693],
                                              [-1.4564354572881797],
                                              [0.5902414894327777]], dtype=object)
1 ab = pd.DataFrame(ab)
2 ab
                                                                  0
                                     0.000305
                     0
                     1
                                     0.004265
                                     0.000315
                     3
                                     0.012186
                      4
                                          0.00153
                      5
                                   -0.000687
                                     0.004503
                     7
                                     0.000562
                     8
                                     0.037402
                     9
                               -0.030643
                    10 -1.456435
                    11 0.590241
1 print("La fórmula del problema es: y =" ,ab.loc[11,0], "+",ab.loc[10,0],"x", "+",ab.loc[9,0],"x","+",ab.loc[8,0],"x","+",ab.loc[7,0],"x","
                La fórmula del problema es: y = 0.5902414894327777 + -1.4564354572881797 x + -0.030643187273626693 x + 0.037401686754168995 x + 0.000562 x + 0.000
              4
1 print("Predicciones")
2\ a = 0.5902414894327777\ +\ -1.4564354572881797* \\ df_regresion['prop_cin_cad']\ +\ -0.030643187273626693* \\ df_regresion['caderas']\ +\ 0.0374016867546693* \\ df_regresion['caderas']\ +\ 0.0374016867546693* \\ df_regresion['caderas']\ +\ 0.0374016867546693* \\ df_regresion['caderas']\ +\ 0.037401686754693* \\ df_regresion['caderas']\ +\ 0.037401686754993* \\ df_regresion['cader
                Predicciones
1 dfPredicciones = pd.DataFrame(a)
1 dfY = pd.DataFrame(Y)
1 dfY
2 dfY = dfY.rename(columns={ 0 :'Casos de Diabetes'})
1 freq = dfY['Casos de Diabetes'].value_counts()
2 freq
                0
                                    330
                Name: Casos de Diabetes, dtype: int64
1 Comparativa = pd.concat([dfY, dfPredicciones], axis =1 )
```

1 Comparativa

	Casos de	Diabetes	0
0		0	-0.035543
1		0	-0.055904
2		0	-0.041148
3		0	0.056836
4		0	-0.020507
385		0	0.225141
386		1	0.988941
387		0	0.208410
388		1	0.566372
389		0	0.241105

390 rows × 2 columns

1 Comparativa.columns

```
Index(['Casos de Diabetes', 0], dtype='object')
```

- 1 Comparativa = Comparativa.rename(columns={0:'Predicción'})
- 2 Comparativa.columns

Index(['Casos de Diabetes', 'Predicción'], dtype='object')

1 Comparativa

	Casos de	Diabetes	Predicción
0		0	-0.035543
1		0	-0.055904
2		0	-0.041148
3		0	0.056836
4		0	-0.020507
385		0	0.225141
386		1	0.988941
387		0	0.208410
388		1	0.566372
389		0	0.241105

390 rows × 2 columns

- 1 Comparativa.loc[Comparativa['Predicción'] > 0.268, 'Predicciones'] = 'True'
 2 Comparativa.loc[Comparativa['Predicción'] < 0.268, 'Predicciones'] = 'False'</pre>
- 1 Comparativa

С	asos de Diabetes	Predicción	Predicciones	
0	0	-0.035543	False	
1	0	-0.055904	False	
2	0	-0.041148	False	
3	0	0.056836	False	
4	0	-0.020507	False	
2 freq 0 330 1 60				
Name: C	asos de Diabetes,	0.0000,2	1140	
<pre>1 freq = Comparativa['Predicciones'].value_counts() 2 freq</pre>				
	328 62 redicciones, dtyp	oe: int64		

▼ Regresion con variables más altas en "power"

1 df_regresion.head()

	colesterol	glucosa	hdl_chol	prop_col_hdl	edad	genero	altura	peso	IMC	ps_sistolica	ps_diastolica	cintura	caderas	prop_cin_
0	193	77	49	3.9	19	0	61	119	22.5	118	70	32	38	
1	146	79	41	3.6	19	0	60	135	26.4	108	58	33	40	
2	217	75	54	4.0	20	0	67	187	29.3	110	72	40	45	
3	226	97	70	3.2	20	0	64	114	19.6	122	64	31	39	
4	164	91	67	2.4	20	0	70	141	20.2	122	86	32	39	
4														>

```
1 df1 = df_regresion.drop(["altura","ps_diastolica","hdl_chol", "IMC", "caderas", "genero"], axis = 1)
2 df1
```

	colesterol	glucosa	prop_col_hdl	edad	peso	ps_sistolica	cintura	prop_cin_cad	diabetes
0	193	77	3.9	19	119	118	32	0.84	0
1	146	79	3.6	19	135	108	33	0.83	0
2	217	75	4.0	20	187	110	40	0.89	0
3	226	97	3.2	20	114	122	31	0.79	0
4	164	91	2.4	20	141	122	32	0.82	0
•••									
385	227	105	5.2	83	125	150	35	0.88	0
386	226	279	4.3	84	192	144	41	0.85	1
387	301	90	2.6	89	115	218	31	0.76	0
388	232	184	2.0	91	127	170	35	0.92	1
389	165	94	2.4	92	217	160	51	1.00	0

390 rows × 9 columns

```
1 df1,test = train_test_split(df1,test_size=.3, random_state = 20)
```

² df1.shape

³ y_test = test['diabetes']

```
1 df2 = df1.drop(['colesterol'], axis=1)
2 df2 = df2.drop(['glucosa'], axis =1)
3 df2 = df2.drop(['prop_col_hd1'], axis =1)
4 df2 = df2.drop(['edad'], axis =1)
5 df2 = df2.drop(['peso'], axis =1)
6 df2 = df2.drop(['ps_sistolica'], axis =1)
7 df2 = df2.drop(['cintura'], axis =1)
8 Y = df2.drop(['prop_cin_cad'], axis =1)
9
10 Y
```

	diabetes
33	0
84	0
87	0
222	0
382	0
331	0
218	0
223	1
271	1
355	0

273 rows × 1 columns

```
1 dfx = df1.drop(['diabetes'], axis=1)
```

1 from numpy import \ast

1 Xn = ones(273)

1 dfx['Xn'] = Xn

2 X = dfx

3 X

	colesterol	glucosa	prop_col_hdl	edad	peso	ps_sistolica	cintura	prop_cin_cad	Xn
33	169	104	2.9	25	154	140	40	0.95	1.0
84	179	85	3.4	32	179	140	37	0.79	1.0
87	213	83	4.5	33	157	130	37	0.90	1.0
222	189	75	2.6	49	205	120	40	0.82	1.0
382	271	121	6.8	81	158	146	36	0.84	1.0
331	170	67	5.2	65	182	140	42	1.08	1.0
218	209	87	6.1	48	121	111	32	0.84	1.0
223	160	196	4.8	49	266	150	49	1.09	1.0
271	219	173	7.1	56	197	100	41	0.82	1.0
355	199	85	3.4	71	171	136	38	0.95	1.0

273 rows × 9 columns

```
1 Xt = X.transpose()
```

2 Xt

```
33
                             84
                                   87
                                          222
                                                  382
                                                         383
                                                                 320
                                                                         171
                                                                                 16
                                                                                       311 ...
                                                                                                     40
                                                                                                           118
                                                                                                                   162
                                                                                                                            71
                 169.00
                        179.00
                                213.0
                                        189.00
                                              271.00
                                                      240.00
                                                              283.00
                                                                     172.00
                                                                             244.00
                                                                                     196.0
                                                                                                 220.00
                                                                                                        227.00
                                                                                                                179.00
                                                                                                                       195.00
                                                                                                                               201.00
      colesterol
       alucosa
                 104.00
                          85.00
                                  83.0
                                         75.00
                                               121.00
                                                        88.00
                                                              145.00
                                                                      101.00
                                                                               89.00
                                                                                     206.0
                                                                                                  60.00
                                                                                                          75.00
                                                                                                                 80.00
                                                                                                                         92.00
                                                                                                                               106.00
     prop_col_hdl
                   2.90
                           3.40
                                   4.5
                                          2.60
                                                 6.80
                                                         4.90
                                                                7.30
                                                                        3.70
                                                                                2.70
                                                                                       4.8
                                                                                                   3.30
                                                                                                           5.20
                                                                                                                   1.90
                                                                                                                          4.80
        edad
                  25.00
                          32.00
                                  33.0
                                         49.00
                                                81.00
                                                        82.00
                                                               63.00
                                                                       42.00
                                                                               21.00
                                                                                      62.0
                                                                                                  26.00
                                                                                                          37.00
                                                                                                                 41.00
                                                                                                                         30.00
                                                                                                                                 58.00
        peso
                 154.00
                        179.00
                                 157.0
                                       205.00
                                              158.00
                                                       170.00
                                                              200.00
                                                                      165.00
                                                                             163.00
                                                                                     196.0
                                                                                                 150.00
                                                                                                        170.00
                                                                                                                118.00
                                                                                                                        191.00
                                                                                                                               215.00
                 140.00
                         140.00
                                 130.0
                                        120.00
                                               146.00
                                                       180.00
                                                               190.00
                                                                      118.00
                                                                             116.00
                                                                                     178.0
                                                                                                 136.00
                                                                                                         140.00
                                                                                                                144.00
                                                                                                                        161.00
                                                                                                                                186.00
     ps_sistolica
                   40.00
                                         40.00
                                                        41.00
                                                                       33.00
                                                                                                                         46.00
                                                                                                                                 46.00
       cintura
                          37.00
                                  37.0
                                                36.00
                                                                44.00
                                                                               34.00
                                                                                       46.0
                                                                                                  33.00
                                                                                                          34.00
                                                                                                                 28.00
    prop_cin_cad
                    0.95
                           0.79
                                   0.9
                                          0.82
                                                 0.84
                                                         0.89
                                                                 0.92
                                                                        0.73
                                                                                0.87
                                                                                        0.9
                                                                                                   0.85
                                                                                                           0.87
                                                                                                                   0.78
                                                                                                                          0.94
         Χn
                    1.00
                           1.00
                                   1.0
                                          1.00
                                                 1.00
                                                         1.00
                                                                1.00
                                                                        1.00
                                                                                1.00
                                                                                       1.0
                                                                                                   1.00
                                                                                                           1.00
                                                                                                                   1.00
                                                                                                                          1.00
   9 rows × 273 columns
1 X = X.to_numpy()
2 X
                              2.9 , ...,
    array([[169. , 104. ,
                                           40.
                                                    0.95,
                                                            1.
                                                                1,
           [179. , 85. ,
                              3.4 , ...,
                                           37.
                                                    0.79,
                                                             1.
                                                                 1,
                                                    0.9 ,
           [213.
                     83.
                              4.5, ...,
                                           37.
                                                             1.
           Γ160.
                 , 196. ,
                              4.8 , ...,
                                           49.
                                                    1.09.
                                                            1.
                                                                 1.
           [219.
                                                            1. ],
                 , 173. ,
                              7.1 , ..., 41.
                                                    0.82,
           [199.
                 , 85.
                              3.4 , ...,
                                           38.
                                                    0.95,
                                                            1.
1 Xt = Xt.to_numpy()
2 Xt
    array([[169. , 179. , 213. , ..., 160. , 219. , 199. ],
           [104. , 85. , 83. , ..., 196. , 173. ,
                      3.4,
                              4.5 , ...,
                                           4.8,
           [ 2.9,
                                                    7.1 ,
                                                            3.4 ],
                                               , 41.
           [ 40.
                     37.
                         , 37. , ..., 49.
                     0.79,
                             0.9 , ...,
                                           1.09,
                                                   0.82,
           [ 0.95,
                                                            0.951.
           [ 1. ,
                      1.,
                              1. , ...,
                                            1. ,
                                                    1. ,
1 A = Xt@X
2 print(A)
    [[1.2196441e+07 6.3338180e+06 2.6720720e+05 2.7043180e+06 1.0094207e+07
      7.8609770e+06 2.1513320e+06 4.9914480e+04 5.6355000e+04]
     [6.3338180e+06 4.1731520e+06 1.4358750e+05 1.4837400e+06 5.4745860e+06
      4.1949200e+06 1.1609460e+06 2.6721420e+04 2.9988000e+04]
     [2.6720720e+05 1.4358750e+05 6.4791700e+03 5.9335200e+04 2.2671140e+05
      1.7238980e+05 4.7850900e+04 1.1006290e+03 1.2377000e+03]
     [2.7043180e+06 1.4837400e+06 5.9335200e+04 6.7273800e+05 2.2684630e+06
      1.8125780e+06 4.8944800e+05 1.1403330e+04 1.2816000e+04]
     [1.0094207e+07 5.4745860e+06 2.2671140e+05 2.2684630e+06 9.1154830e+06
      6.7395260e+06 1.8998920e+06 4.3172470e+04 4.8613000e+04]
     [7.8609770e+06 4.1949200e+06 1.7238980e+05 1.8125780e+06 6.7395260e+06
      5.3356950e+06 1.4373650e+06 3.3360480e+04 3.7683000e+04]
     [2.1513320e+06 1.1609460e+06 4.7850900e+04 4.8944800e+05 1.8998920e+06
      1.4373650e+06 4.0231900e+05 9.2156900e+03 1.0361000e+04]
     [4.9914480e+04 2.6721420e+04 1.1006290e+03 1.1403330e+04 4.3172470e+04
      3.3360480e+04 9.2156900e+03 2.1467790e+02 2.4123000e+02]
     [5.6355000e+04 2.9988000e+04 1.2377000e+03 1.2816000e+04 4.8613000e+04
      3.7683000e+04 1.0361000e+04 2.4123000e+02 2.7300000e+02]]
```

1 A = pd.DataFrame(A)

2 A

278

3.80

1.05

1.00

331

170.00 2

67.00

5.20

65.00

182 00 1

140.00 1

42.00

1.08

1.00

```
0 12196441.00 6333818.00 267207.200 2704318.00
                                                       10094207.00 7860977.00 2151332.00 49914.4800 56355.00
       6333818.00 4173152.00 143587.500 1483740.00
                                                        5474586.00 4194920.00 1160946.00 26721.4200 29988.00
1 A = A.to numpy()
2 A
   array([[1.2196441e+07, 6.3338180e+06, 2.6720720e+05, 2.7043180e+06,
            1.0094207e+07, 7.8609770e+06, 2.1513320e+06, 4.9914480e+04,
            5.6355000e+04],
           [6.3338180e+06, 4.1731520e+06, 1.4358750e+05, 1.4837400e+06,
            5.4745860e+06, 4.1949200e+06, 1.1609460e+06, 2.6721420e+04,
           2.9988000e+04],
           [2.6720720e+05, 1.4358750e+05, 6.4791700e+03, 5.9335200e+04,
            2.2671140e+05, 1.7238980e+05, 4.7850900e+04, 1.1006290e+03,
           1.2377000e+03],
           [2.7043180e+06, 1.4837400e+06, 5.9335200e+04, 6.7273800e+05,
            2.2684630e+06, 1.8125780e+06, 4.8944800e+05, 1.1403330e+04,
           1.2816000e+04],
           [1.0094207e+07, 5.4745860e+06, 2.2671140e+05, 2.2684630e+06,
            9.1154830e+06, 6.7395260e+06, 1.8998920e+06, 4.3172470e+04,
           4.8613000e+04],
           [7.8609770e+06, 4.1949200e+06, 1.7238980e+05, 1.8125780e+06,
            6.7395260e+06, 5.3356950e+06, 1.4373650e+06, 3.3360480e+04,
           3.7683000e+04],
           [2.1513320e+06, 1.1609460e+06, 4.7850900e+04, 4.8944800e+05,
            1.8998920e+06, 1.4373650e+06, 4.0231900e+05, 9.2156900e+03,
           [4.9914480e+04, 2.6721420e+04, 1.1006290e+03, 1.1403330e+04,
            4.3172470e+04, 3.3360480e+04, 9.2156900e+03, 2.1467790e+02,
            2.4123000e+02],
           [5.6355000e+04, 2.9988000e+04, 1.2377000e+03, 1.2816000e+04,
            4.8613000e+04, 3.7683000e+04, 1.0361000e+04, 2.4123000e+02,
           2.7300000e+0211)
1 Ainversa = np.linalg.inv(A)
2 Ainversa
    array([[ 2.73868442e-06, -2.23419931e-08, -3.49228307e-05,
            -9.69025896e-07, 3.56421918e-07, -9.58889852e-07,
            -1.83392977e-06, 6.30974423e-05, -2.76329991e-04],
           [-2.23419931e-08, 1.38174839e-06, -7.24140443e-06,
            -1.37103447e-06, -3.06152046e-07, 6.81812754e-08,
            -1.52428103e-07, -5.00408284e-05, 4.51334337e-05],
           [-3.49228307e-05, -7.24140443e-06, 1.82413497e-03,
            -2.83050776e-06, -2.29117676e-05, 8.41352645e-06,
             4.49415183e-05, -3.30928607e-03, 4.00438880e-03],
           [-9.69025896e-07, -1.37103447e-06, -2.83050776e-06,
             2.19566191e-05, 4.33456771e-06, -5.54275016e-06,
            -2.15725022e-05, -3.79731260e-04, 4.80211379e-04],
           [ 3.56421918e-07, -3.06152046e-07, -2.29117676e-05, 4.33456771e-06, 1.05249690e-05, -3.24881192e-07,
            -7.02558435e-05, 1.20323628e-03, -3.65724932e-04],
           [-9.58889852e-07, 6.81812754e-08, 8.41352645e-06,
            -5.54275016e-06, -3.24881192e-07, 9.96920286e-06,
            -4.60800475e-06, 1.30633441e-04, -8.46260469e-04],
           [-1.83392977e-06, -1.52428103e-07, 4.49415183e-05,
            -2.15725022e-05, -7.02558435e-05, -4.60800475e-06,
            6.36879407e-04, -1.40317690e-02, 2.57852766e-03],
           [ 6.30974423e-05, -5.00408284e-05, -3.30928607e-03,
            -3.79731260e-04, 1.20323628e-03, 1.30633441e-04,
            -1.40317690e-02, 1.07564987e+00, -6.24923579e-01],
           [-2.76329991e-04, 4.51334337e-05, 4.00438880e-03,
             4.80211379e-04, -3.65724932e-04, -8.46260469e-04,
             2.57852766e-03, -6.24923579e-01, 6.51323456e-01]])
1 Nueva = Ainversa@Xt
2 Nueva
   \verb"array" ([[-3.40879719e-05, -2.62044800e-05, 3.62596697e-05, \ldots,
            -1.27742965e-04, -3.17659007e-05, 2.30436085e-08],
           [ 3.85455870e-05, -3.38980087e-07, -1.26496428e-05, ...,
             7.72192356e-05, 5.03142495e-05, -6.02386335e-05],
           [-1.12812646e-03, -6.25647131e-04, 2.61079547e-04, ...,
            -6.22915032e-04, 3.35309786e-03, -1.76939776e-03],
           [ 2.52423405e-03, 9.58302863e-04, 9.72331290e-04, ...,
            -2.05290264e-03, 1.56635513e-03, -9.47428183e-04],
           [ 2.56291149e-02, -7.70296616e-02, 1.17397400e-02, ...,
             1.65430146e-01, -1.07691930e-01, 5.73465538e-02],
```

2 ab

```
[-3.23988224e-02, 5.24530828e-02, -4.38040515e-03, ..., -1.20332514e-01, 9.05467103e-02, -2.54436768e-02]])
1 Y = Y.to_numpy()
2 Y
    array([[0],
             [0],
             [0],
             [0],
             [0],
             [0],
             [1],
             [0],
             [0],
             [1],
             [0],
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             [0],
             [0],
             [0],
             [1],
             [0],
            [0],
[1],
1 ab = Nueva@Y
2 ab
    array([[0.00047391011039231564],
             [0.004326064840941465],
             [0.010772014850325277],
             [0.000433571324178371],
             [-0.00045627172354809737],
             [0.0007264512732575491],
             [0.003952395309539705],
             [0.19105615281791233],
             [-0.8152372863441626]], dtype=object)
1 ab= pd.DataFrame(ab)
```

```
0
                    0 0.000474
                                  0.004326
                             0.010772
                                 0.000434
                               -0.000456
                             0.000726
                     6 0.003952
                    7 0.191056
                     8 -0.815237
1 \; print("La \; f\'ormula \; del \; problema \; es: \; y \; =", \; ab.loc[8,0],"+",ab.loc[7,0],"x","+",ab.loc[6,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[4,0],"x","+",ab.loc[4,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x","+",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5,0],"x",ab.loc[5
                1 print("Predicciones")
2 \ a = ab.loc[8,0] \ + \ ab.loc[7,0] \ * test['prop\_cin\_cad'] \ + \ ab.loc[6,0] \ * test['cintura'] \ + \ ab.loc[5,0] \ * test['ps\_sistolica'] \ + \ ab.loc[4,0] \ + 
                Predicciones
1 dfPredicciones = pd.DataFrame(a)
1 dfY = pd.DataFrame(y_test)
1 dfY
2 dfY = dfY.rename(columns={ 0 :'Casos de Diabetes'})
1 Comparativa = pd.concat([dfY, dfPredicciones], axis =1 )
1 Comparativa
                                          diabetes
                                                                                                                  0
                                                                        0 -0.486479
                      10
                     378
                                                                        0 -0.468800
                                                                        0 -0.515969
                      17
                     122
                                                                        0 -0.483663
                     205
                                                                        0 -0.434135
                       ...
                     185
                                                                        0 -0.484122
                     261
                                                                        0 -0.431762
                     108
                                                                        0 -0.511853
                      21
                                                                        0 -0.527060
                     319
                                                                        0 -0.463043
                117 rows × 2 columns
1 Comparativa.columns
                Index(['diabetes', 0], dtype='object')
1 Comparativa = Comparativa.rename(columns={0:'Predicción'})
2 Comparativa.columns
                Index(['diabetes', 'Predicción'], dtype='object')
```

1 Comparativa

	diabetes	Predicción
10	0	-0.486479
378	0	-0.468800
17	0	-0.515969
122	0	-0.483663
205	0	-0.434135
185	0	-0.484122
261	0	-0.431762
108	0	-0.511853
21	0	-0.527060
319	0	-0.463043

117 rows × 2 columns

```
1 Comparativa['Predicción'].max()
```

-0.37682111871614155

1 Comparativa['Predicción'].min()

-0.5449043640453016

```
1 Comparativa.loc[Comparativa['Predicción'] > 0.268, 'Predicciones'] = 1 2 Comparativa.loc[Comparativa['Predicción'] < 0.268, 'Predicciones'] = 0
```

1 Comparativa

	diabetes	Predicción	Predicciones
10	0	-0.486479	0.0
378	0	-0.468800	0.0
17	0	-0.515969	0.0
122	0	-0.483663	0.0
205	0	-0.434135	0.0
185	0	-0.484122	0.0
261	0	-0.431762	0.0
108	0	-0.511853	0.0
21	0	-0.527060	0.0
319	0	-0.463043	0.0

117 rows × 3 columns

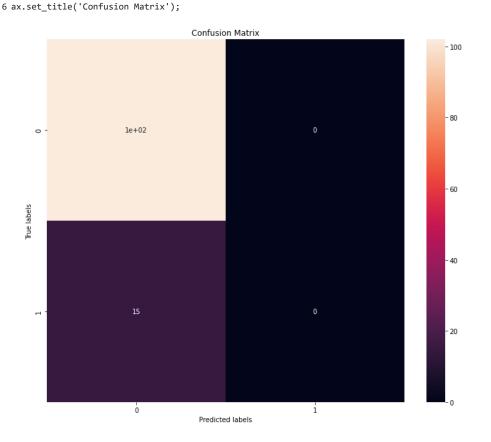
```
1 freq = Comparativa['diabetes'].value_counts()
2 freq
0    102
1    15
Name: diabetes, dtype: int64

1 freq = Comparativa['Predicciones'].value_counts()
2 freq
0.0    117
Name: Predicciones, dtype: int64

1 Comparativa.drop(['Predicción'], axis = 1)
```

	diabetes	Predicciones
10	0	0.0
378	0	0.0
17	0	0.0
122	0	0.0
205	0	0.0
185	0	0.0
261	0	0.0
108	0	0.0
21	0	0.0
319	0	0.0
117 rc	we v 2 colu	mne

117 rows × 2 columns



Análisis discriminante

```
1 from sklearn import preprocessing
 2 df_discriminante_diabetes = df_discriminante['diabetes']
 3 df_discriminante = df_discriminante.drop(['genero','diabetes'], axis = 1)
 4 z_scaler = preprocessing.StandardScaler()
 5 df_stan1 = pd.DataFrame(z_scaler.fit_transform(df_discriminante))
 6 df_stan1 = df_stan1.set_axis(['colesterol', 'glucosa', 'hdl_chol', 'prop_col_hdl', 'edad', 'altura', 'peso', 'IMC', 'ps_sistolica', 'ps_diasto
 8 X = df_stan1[['colesterol', 'glucosa', 'hdl_chol', 'prop_col_hdl', 'edad', 'altura', 'peso', 'IMC', 'ps_sistolica', 'ps_diastolica', 'cintur
9 y = df_discriminante_diabetes
10 model = LinearDiscriminantAnalysis()
11 model.fit(X, y)
12 cv = RepeatedStratifiedKFold(n_splits=12, n_repeats=5, random_state=40)
13 scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
14 print(np.mean(scores))
15 new = [199,77,49,3.9,19,61,119,22.5,118,70, 32, 38, 0.84]
16 model.predict([new])
    0.9215909090909091
    /usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feature names, but LinearDiscriminantAnal
       "X does not have valid feature names, but"
    array(['Diabetes'], dtype='<U11')</pre>
 2 from sklearn.model_selection import cross_val_predict
 3 y_pred = cross_val_predict(model, X, y, cv=13)
 2 from sklearn.metrics import accuracy_score
 3 accuracy_score(y, y_pred)
    0.9230769230769231
 1 cm
    array([[ 37, 23],
            [ 7, 323]])
 1 from sklearn.metrics import confusion_matrix
 2 cm = confusion_matrix(y, y_pred)
 3 import seaborn as sns
 4 ax= plt.subplot()
 5 sns.heatmap(cm, annot=True, ax = ax); #annot=True to annotate cells
7 # labels, title and ticks
 8 ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
 9 ax.set_title('Confusion Matrix');
```

