Gregorio García Velasco

Pablo de la Iglesia

Proyecto Final

- **Introducción**

La hipertensión arterial es una de las principales causas de enfermedades cardiovasculares a nivel mundial, y su detección temprana es clave para prevenir complicaciones graves en la salud de los pacientes.
Este trabajo presenta el desarrollo de una red neuronal diseñada para predecir la presencia de hipertensión sintomática, representada en el dataset como la variable SIM_GIPERT, a partir de datos clínicos disponibles en un conjunto de datos obtenido del repositorio de *UCI* . A través del procesamiento y análisis de los atributos contenidos en dicho dataset, se entrena un modelo supervisado que busca clasificar correctamente si un paciente presenta o no esta condición médica.
El objetivo de este proyecto es evaluar la eficacia de la red neuronal en la detección de hipertensión sintomática.

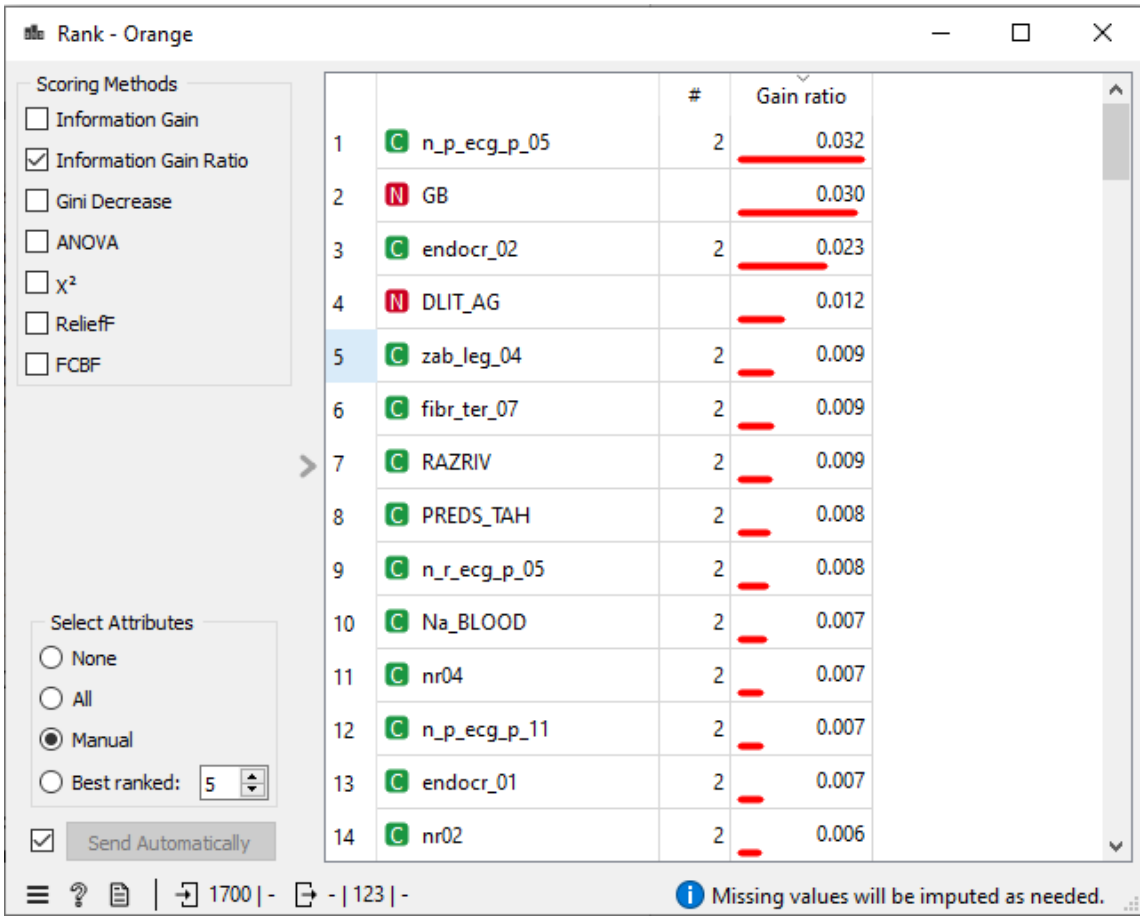
- **Materiales (Explicar punto 1-3)**

Realizar el preprocesamiento de los datos (eliminar duplicados, transformar datos, seleccionar variables, balancear los datos).

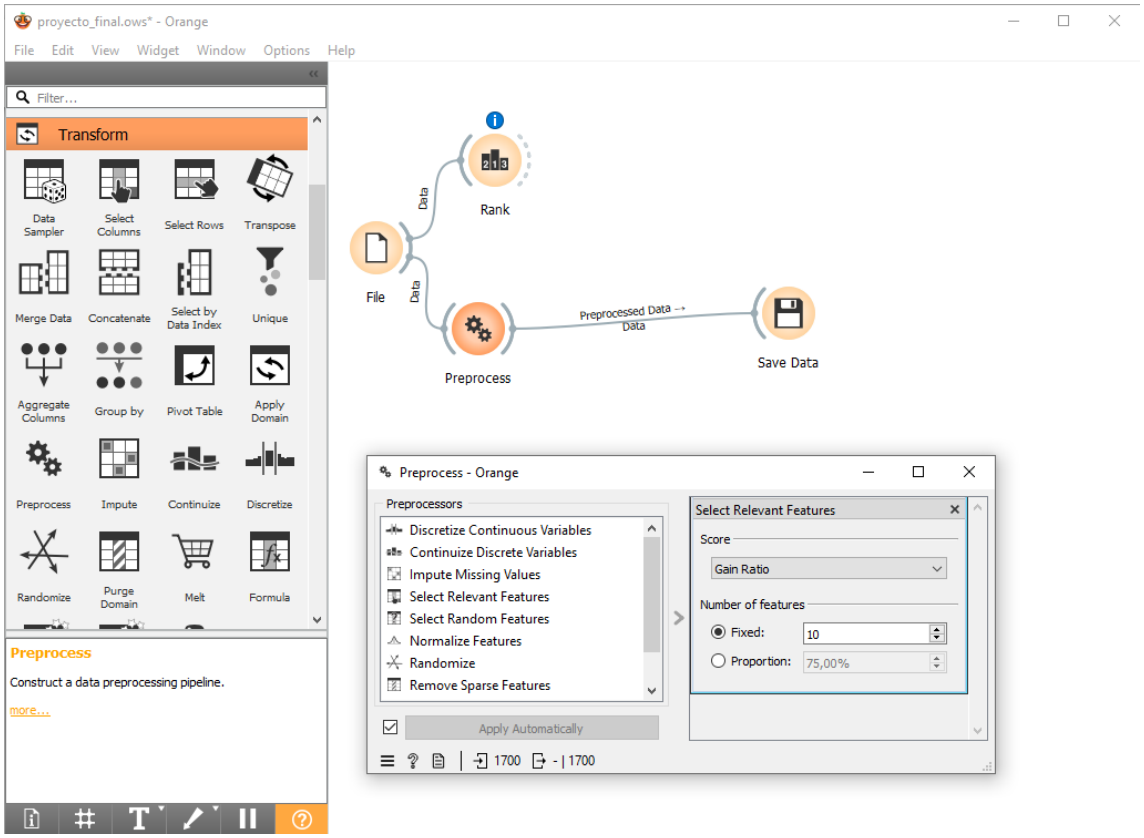
Empezamos el preprocesamiento poniendo las cabeceras de las columnas en el .data y convirtiéndolo a csv.

```
ID,AGE,SEX,INF_ANAM,STENOK_AN,FK_STENOK,IBS_POST,IBS_NASL,GB,SIM_GIPERT,DLIT_AG,ZSN_A,nr11,nr01,nr02,nr03,nr04
_n,ANT_CA_S_n,GEPAR_S_n,ASP_S_n,TIKL_S_n,TRENT_S_n,FIBR_PREDS,PREDS_TAH,JELUD_TAH,FIBR_JELUD,A_V_BLOK,OTEK_LAN
1,77,1,2,1,1,2,?,3,0,7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,?,?,180,100,0,0,0,0,0,0,1,0,0,0,0,0,0,0
2,55,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,?,?,120,90,0,0,0,0,0,0,4,1,0,0,0,1,0,0,0,
3,52,1,0,0,0,2,?,2,0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,150,100,180,100,0,0,0,0,0,0,4,1,0,0,0,1,0
4,68,0,0,0,0,2,?,2,0,3,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,?,?,120,70,0,0,0,0,0,0,0,1,1,0,0,1,0,0,0,
5,60,1,0,0,0,2,?,3,0,7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,190,100,160,90,0,0,0,0,0,0,4,1,0,0,0,0,0,
6,64,1,0,1,2,1,?,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,?,?,140,90,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,
7,70,1,1,1,2,1,?,2,0,7,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,120,80,120,80,0,0,0,0,0,0,0,0,3,0,0,1,0,0
8,65,1,0,1,1,2,?,2,0,7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,?,?,145,95,0,0,0,0,0,0,0,0,2,0,0,1,0,0,0,
9,60,1,0,0,0,2,?,2,0,6,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,200,120,195,120,0,0,0,0,0,0,0,0,3,2,0,1,0
10,77,0,2,0,0,0,?,3,0,6,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,?,?,200,100,0,0,0,0,0,0,4,1,0,0,0,0,0,
11,71,1,0,0,0,0,?,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,140,80,140,90,0,0,0,0,0,0,0,0,3,1,0,1,0,
12,50,0,0,0,0,0,?,2,0,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,140,90,130,80,0,0,0,0,0,0,1,1,0,0,0,1,0,
13,60,1,1,0,0,2,?,2,0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,120,80,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0
14,57,1,0,0,0,2,0,2,0,6,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,140,90,125,80,0,0,0,0,0,0,0,1,3,3,0,1,0,
15,55,1,1,1,2,2,?,2,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,140,80,160,100,0,0,0,0,0,0,0,0,2,1,0,1,0
16,57,1,3,0,0,0,?,2,0,6,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,?,?,115,80,0,0,0,0,0,0,4,1,0,0,0,1,0,0,0
17,52,1,0,6,2,1,?,2,0,7,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,80,60,110,70,0,0,0,0,0,0,0,1,0,0,0,0
18,52,0,1,1,2,2,?,2,0,7,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,150,85,150,90,1,0,0,0,0,0,4,2,0,0,0,1,0,
19,54,1,0,1,3,2,?,2,0,2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,?,?,130,80,0,0,0,0,0,0,4,0,0,0,0,1,0,0,0
20,71,0,0,1,4,2,?,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,?,?,120,80,0,0,0,0,0,0,0,0,2,0,0,1,0,0,0
```

Nos metemos en Orange para ver cuáles son las 10 variables que más impacto tienen sobre nuestro target (SIM_GIPERT).



De aquí cogemos hasta Na_BLOOD (incluido).



Y preprocesamos el dataset cortado con las variables más influyentes. (Datos ausentes)

```python
import pandas as pd

df = pd.read_csv('hipertension_cortada.csv')

for col in df.columns:
    if df[col].isnull().any():
        moda = df[col].mode()[0]
        df[col].fillna(moda, inplace=True)

df.to_csv('hipertension_preprocesado.csv', index=False)
```

El dataset quedaría de la siguiente forma:

```
SIM_GIPERT,n_p_ecg_p_05,GB,endocr_02,DLIT_AG,zab_leg_04,fibr_ter_07,RAZRIV,PREDS_TAH,n_r_ecg_p_05,Na_BLOOD
0.0,0.0,3.0,0.0,7.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,0.0,0.0,0.0,0.0,0.0,0,0,0,1.0,0.0
0.0,0.0,2.0,0.0,2.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,3.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,3.0,0.0,7.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,0.0,0.0,0.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,7.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,7.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,6.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,3.0,0.0,6.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,0.0,0.0,0.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,3.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,2.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,0.0,6.0,0.0,0.0,0,0,0,0.0,0.0
0.0,0.0,2.0,1.0,1.0,0.0,0.0,0,1,0,0.0,0.0
0.0,0.0,2.0,0.0,6.0,0.0,0.0,0,0,0,0.0,1.0
```

Lo metemos en Weka.

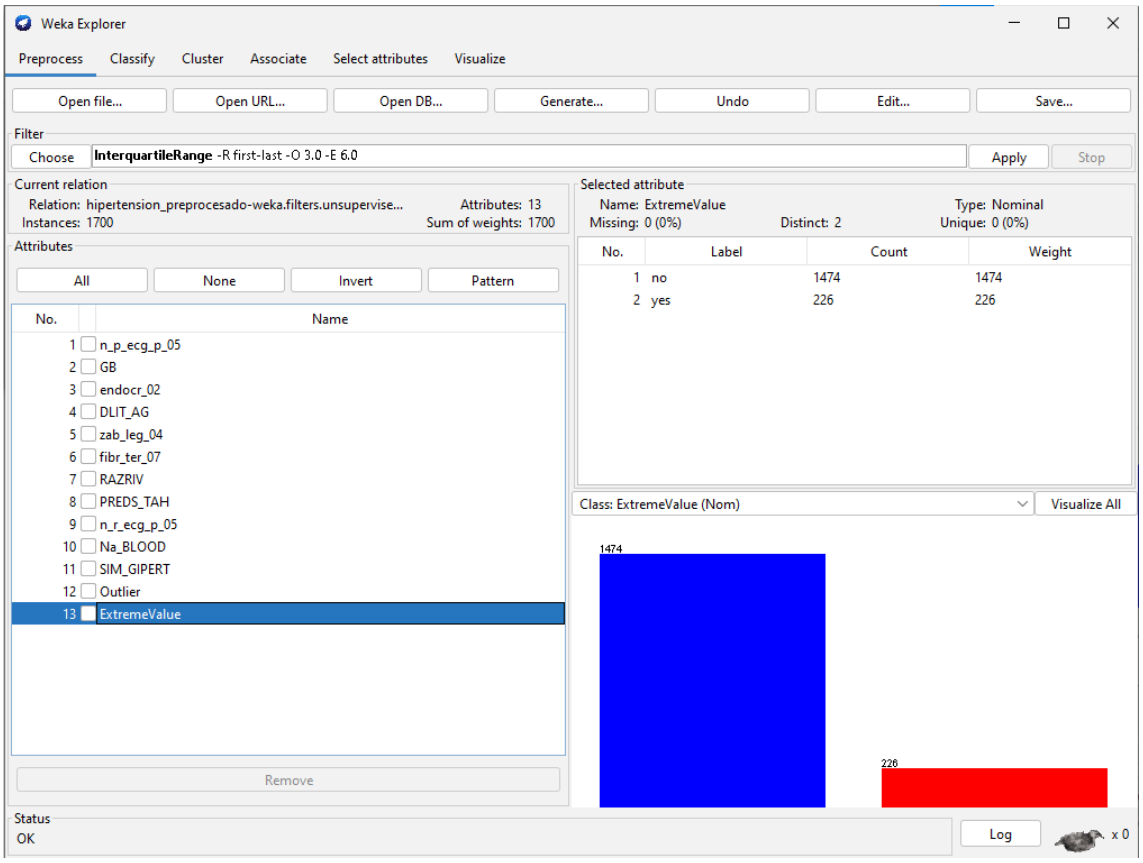
File Edit View ARFF-Viewer - C:\Users\goyo\OneDrive - CUNEF\Escritorio\Uni\Tercero\Segundo cuatri\Redes neuronales\Proyecto Final\hipertension_p...

hipertension_preprocesado.csv

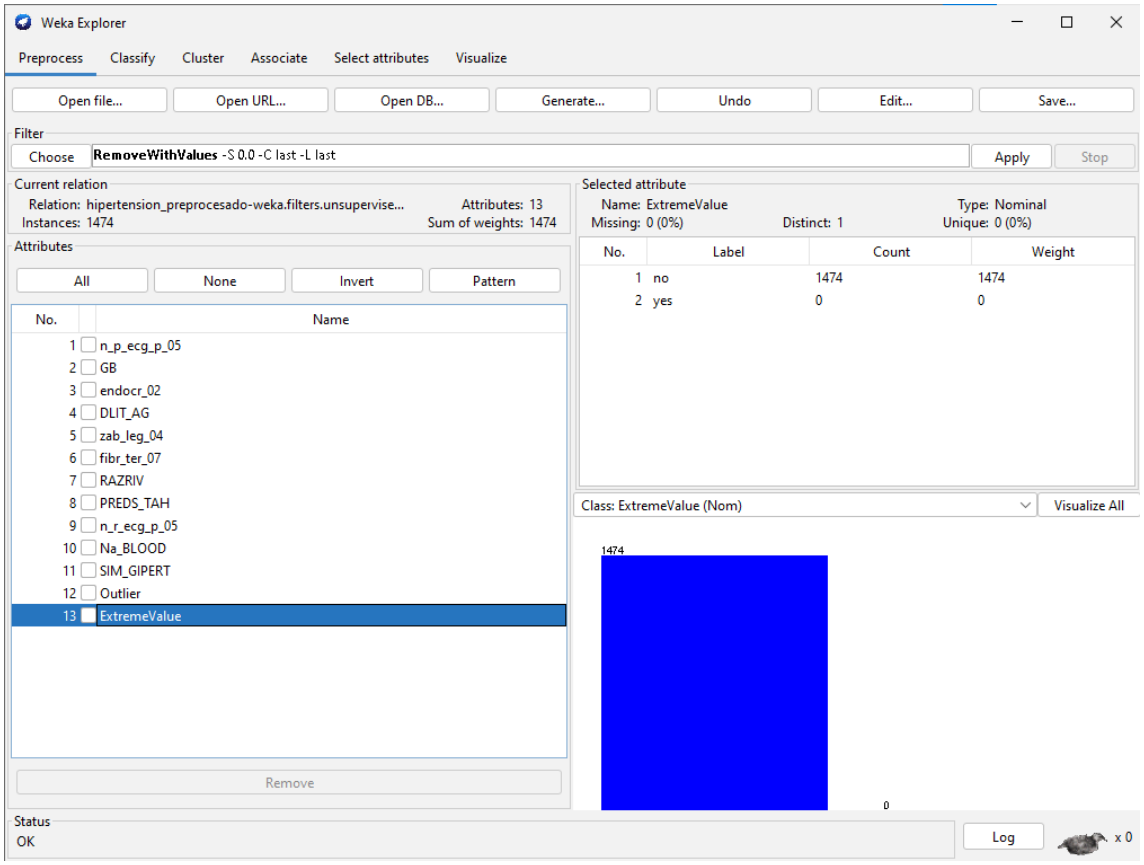
Relation: hipertension_preprocesado

No.	1: SIM_GIPERT Numeric	2: n_p_ecg_p_05 Numeric	3: GB Numeric	4: endocr_02 Numeric	5: DLIT_AG Numeric	6: zab_leg_04 Numeric	7: fibr_ter_07 Numeric	8: RAZRIV Numeric	9: PREDS_TAH Numeric	10: n_r_ecg_p_05 Numeric	11: **Na_BLOOD** Numeric
1	0.0	0.0	3.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
3	0.0	0.0	2.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	2.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	3.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	2.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	2.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	2.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	3.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12	0.0	0.0	2.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0
13	0.0	0.0	2.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0
14	0.0	0.0	2.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.0
15	0.0	0.0	2.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0
16	0.0	0.0	2.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	1.0
17	0.0	0.0	2.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
18	0.0	0.0	2.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.0	2.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

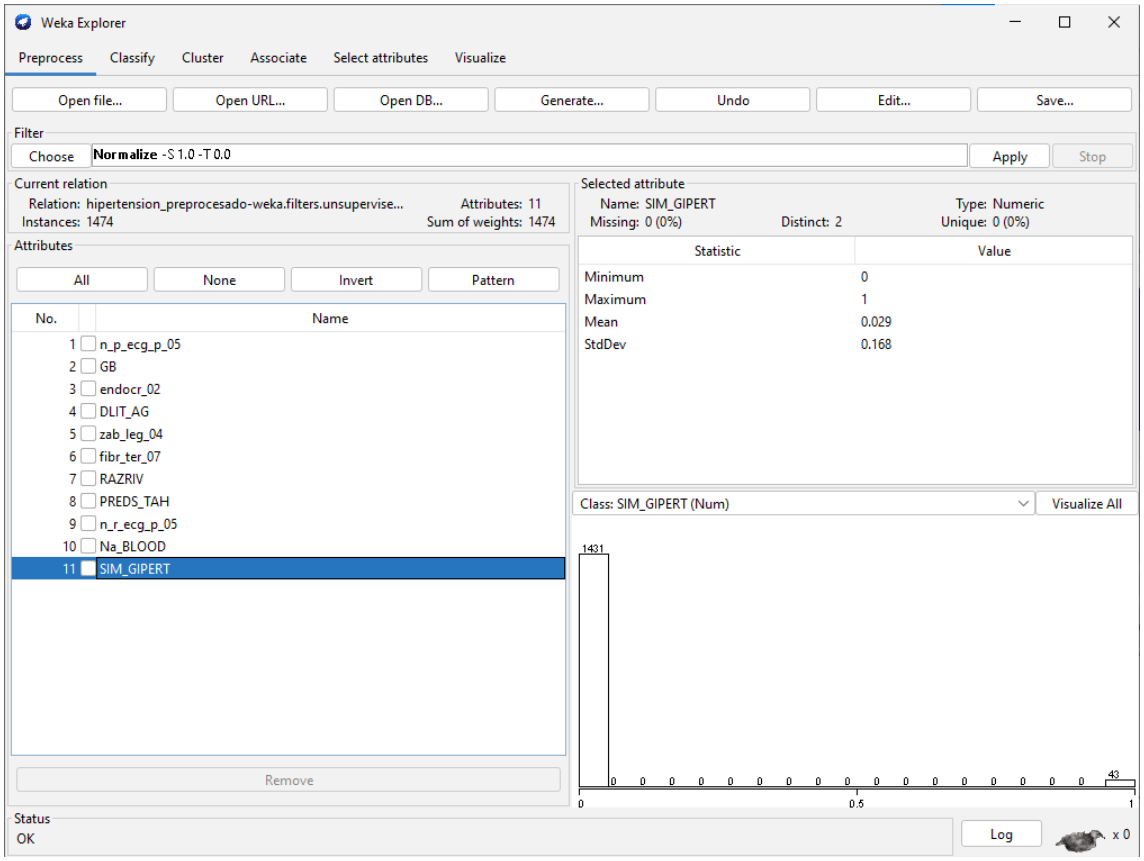
Sacamos los outliers y extreme values.



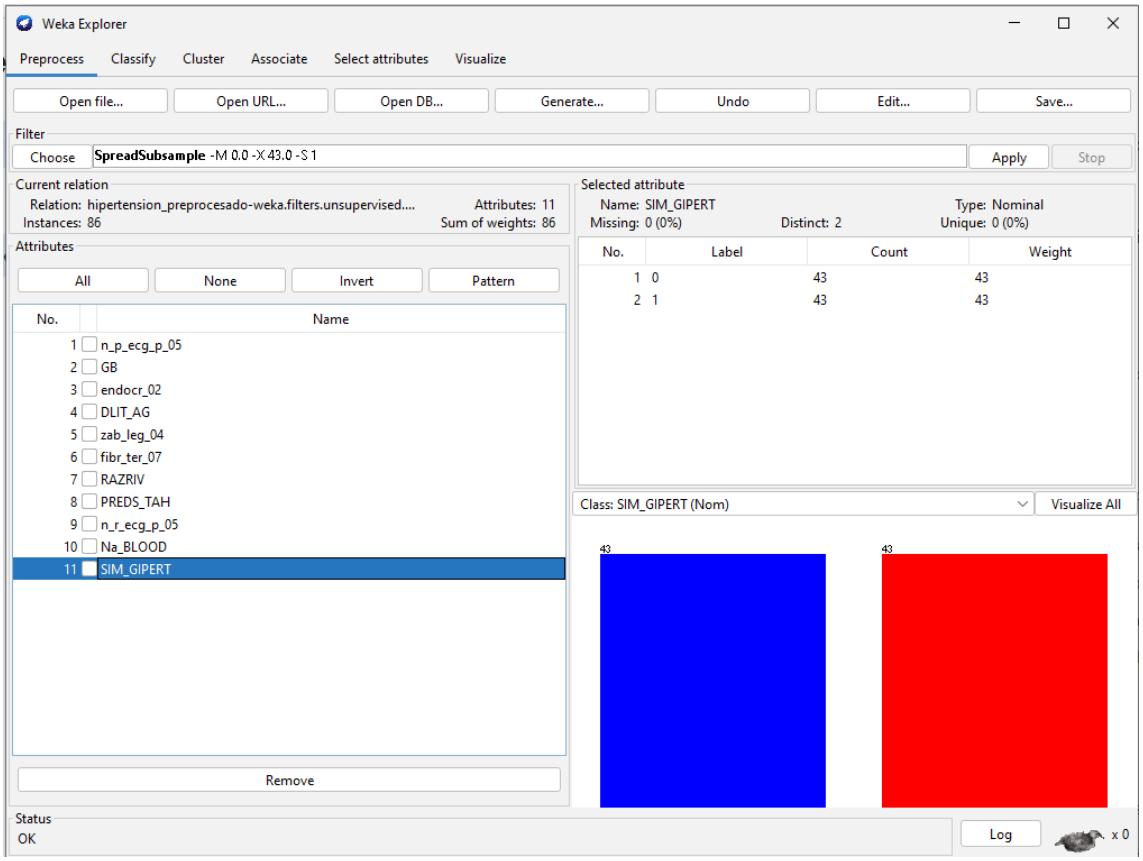
Los eliminamos.



Normalizamos los datos.



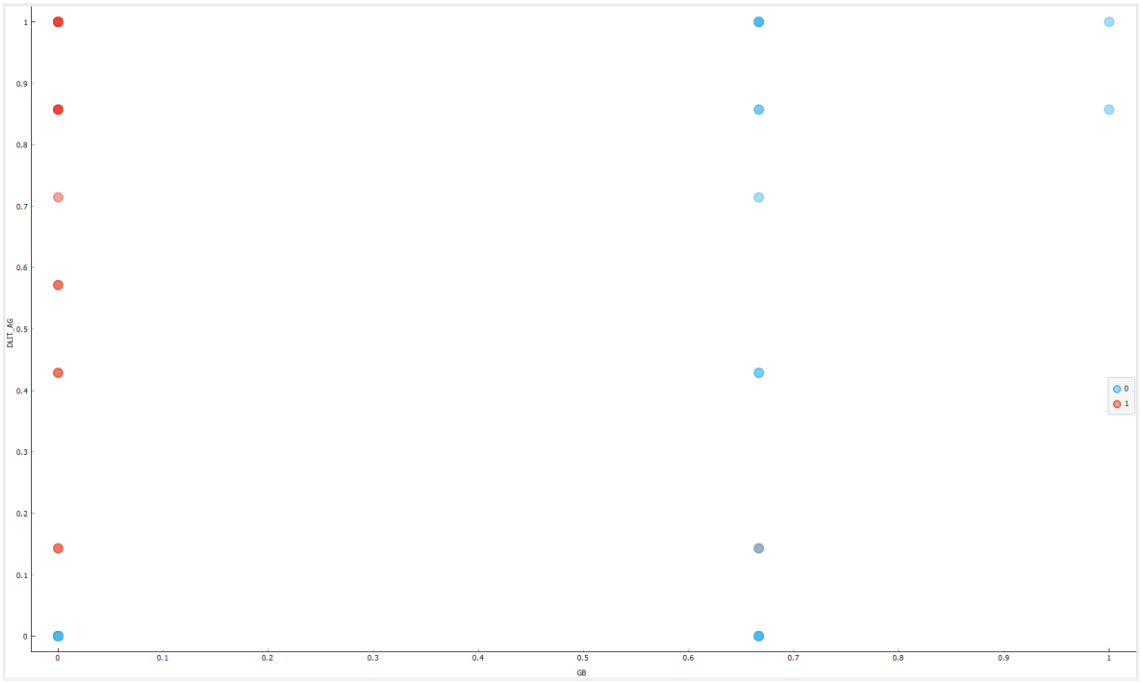
Convertimos la clase target a nominal para poder balancear los datos y los balanceamos.



Visualización de datos (diagramas dispersión, histogramas, barras) de todas las variables.

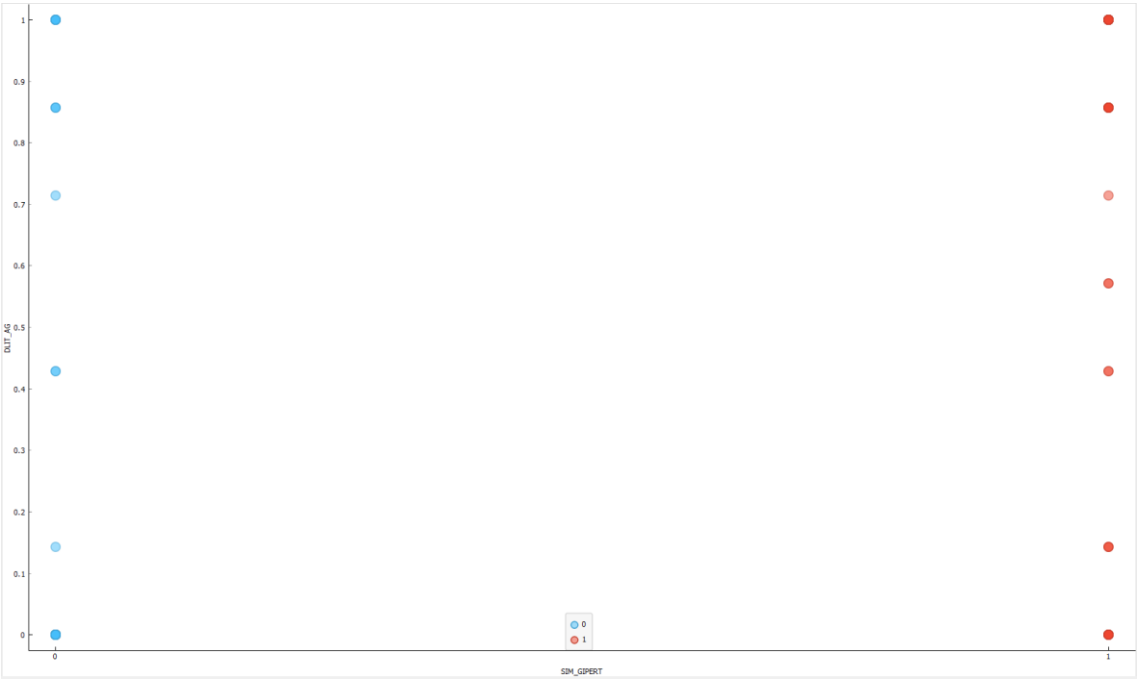
- Diagramas de dispersión

x: GB, y: DLIT_AG

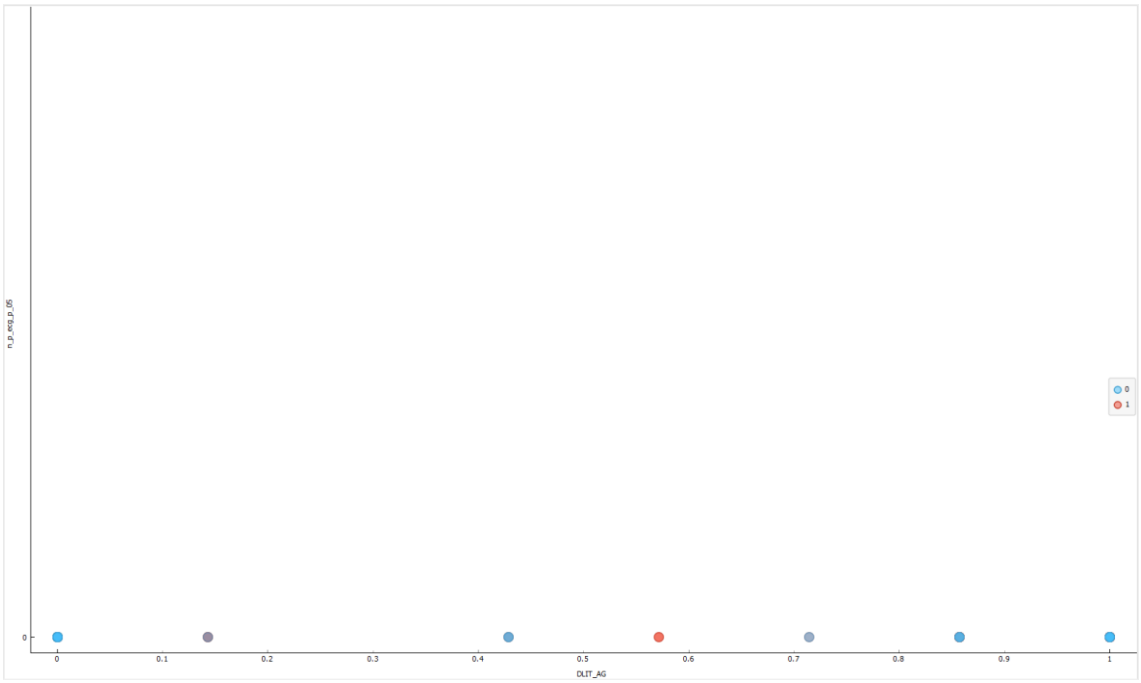


x: n_p_ecg_p_05, y: GB

x: SIM_GIMPERT, y: DLIT_AG



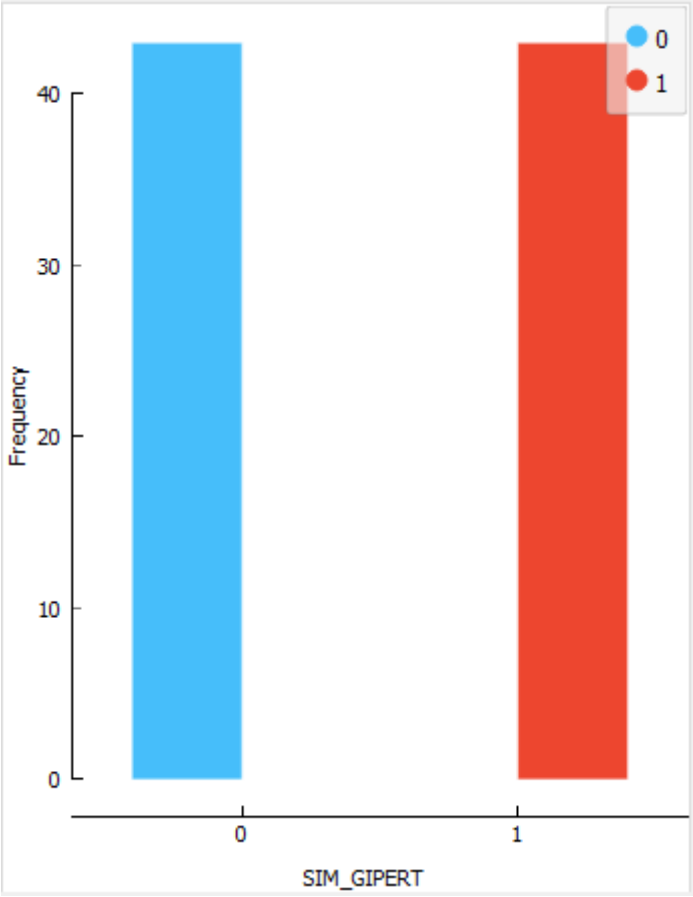
x: DLIT_AG, y: n_p_ecg_p_05

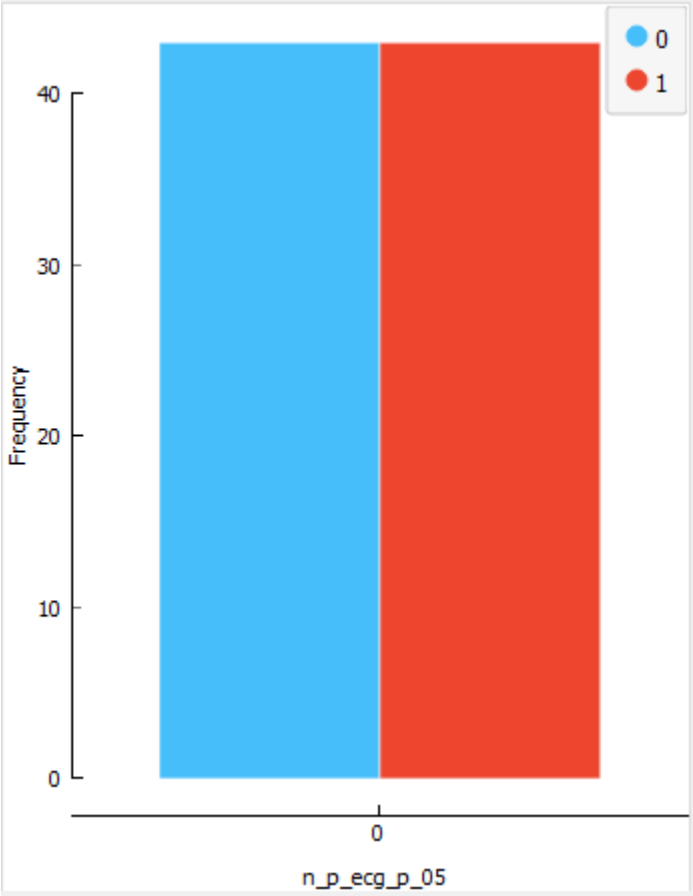


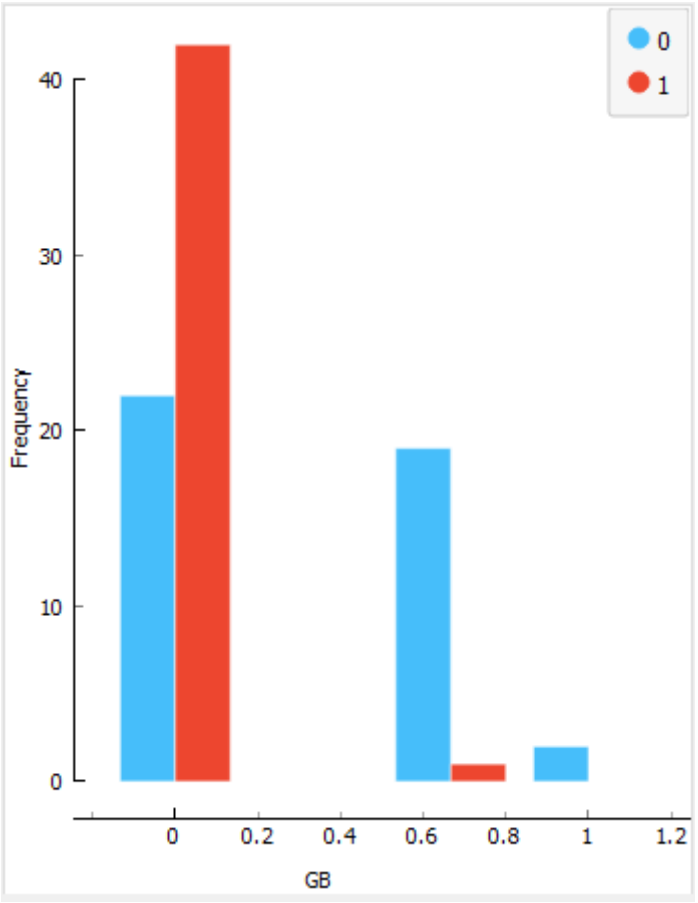
x: endocr_02, y: zab_leg_04

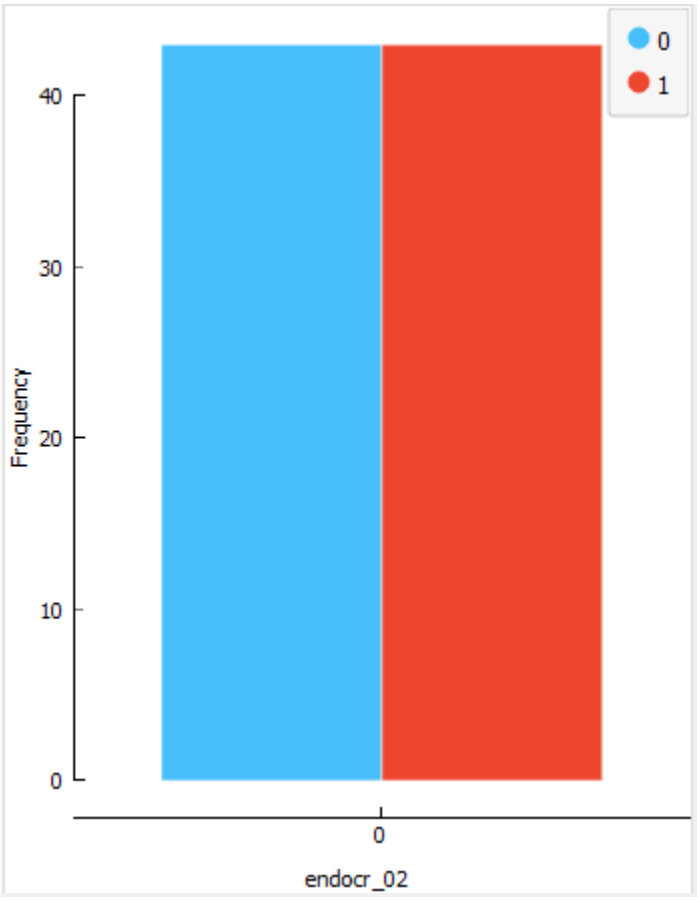
El resto de los gráficos no aportan información útil y son muy parecidos a este último, por lo que hemos decidido no ponerlos.

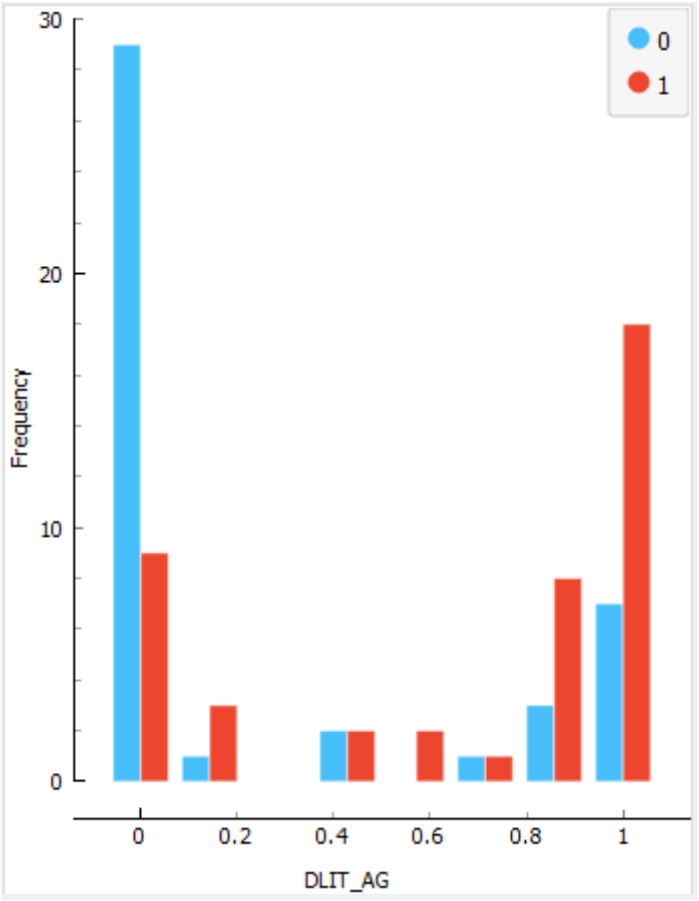
- Histogramas

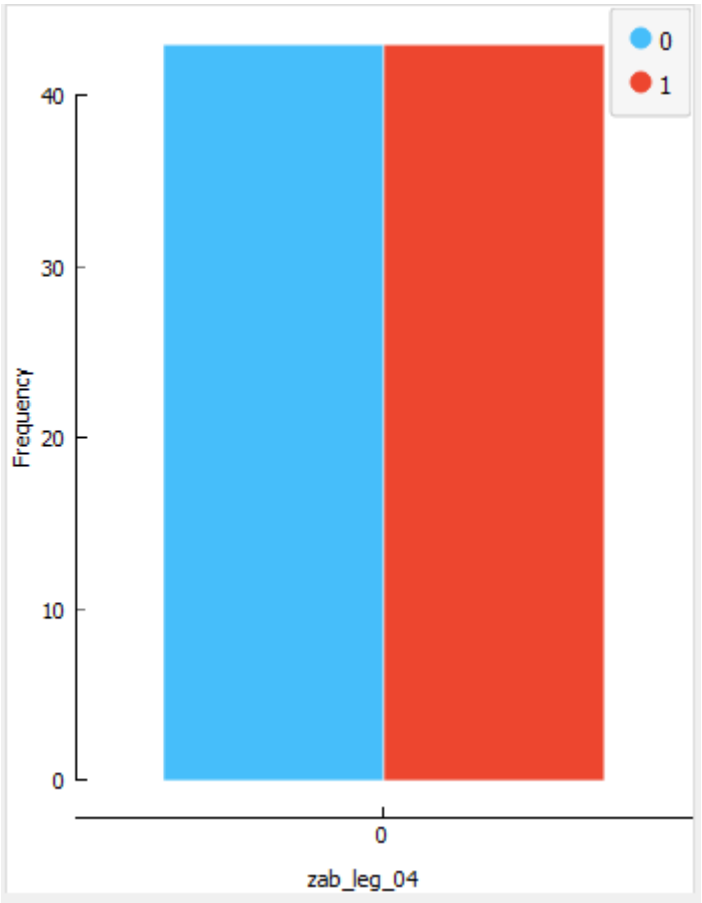

0
1
40
30
20
10
0
Frequency
0
1
SIM_GIPERT

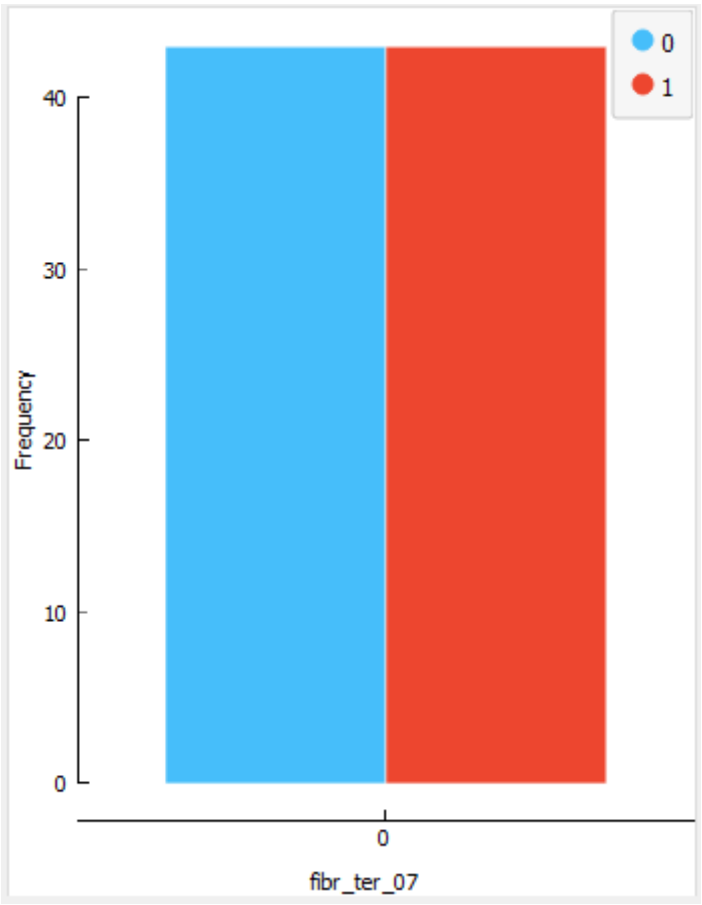

0
1
40
30
20
10
0
Frequency
0
n_p_ecg_p_05

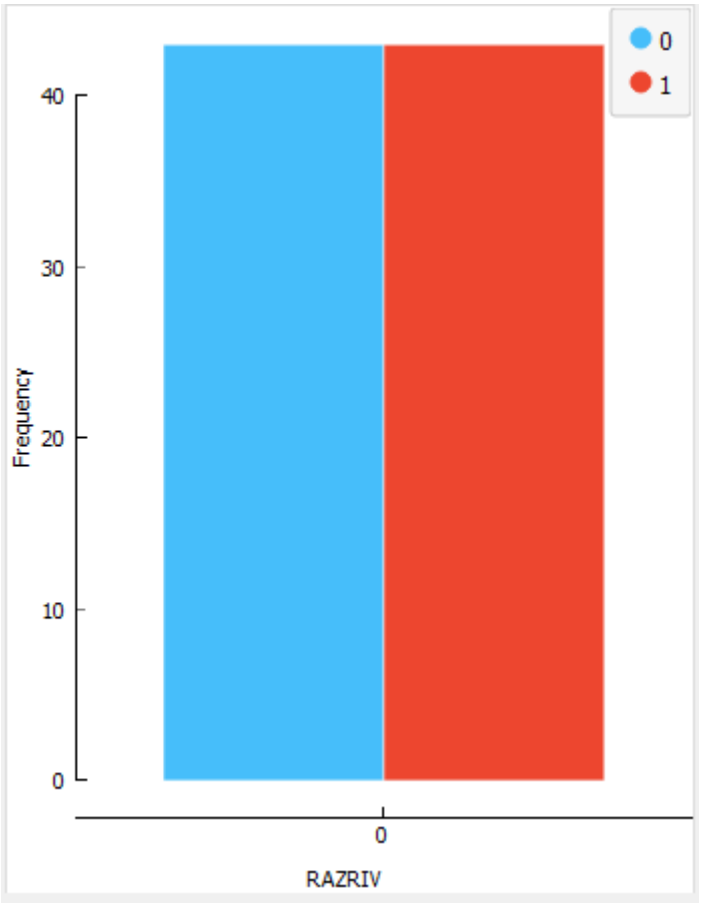

0
1
40
30
20
10
0
Frequency
0
0.2
0.4
0.6
0.8
1
1.2
GB

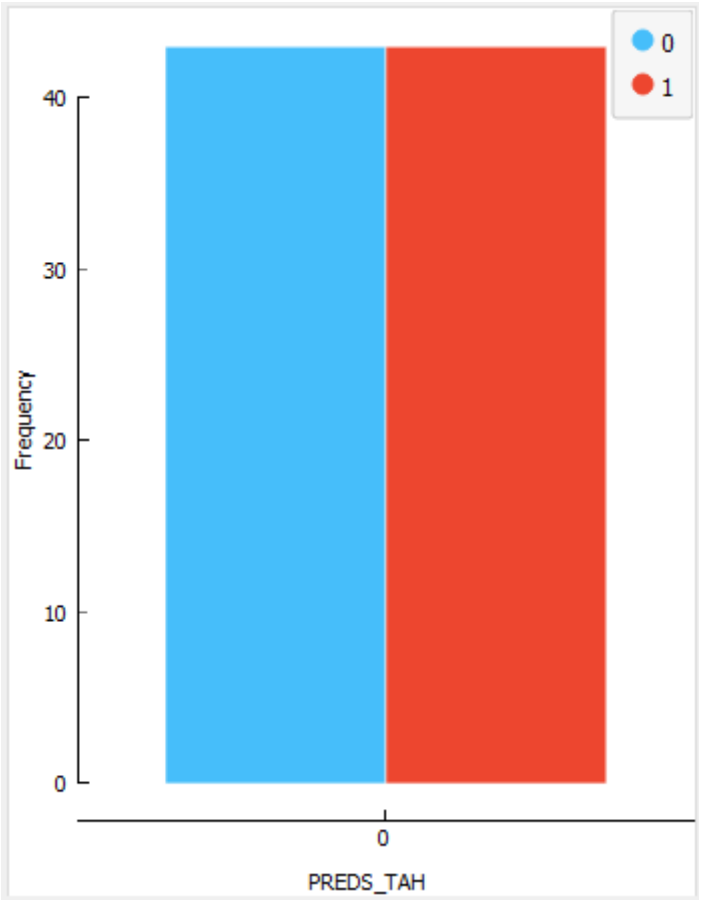

0
1
40
30
20
10
0
Frequency
0
endocr_02

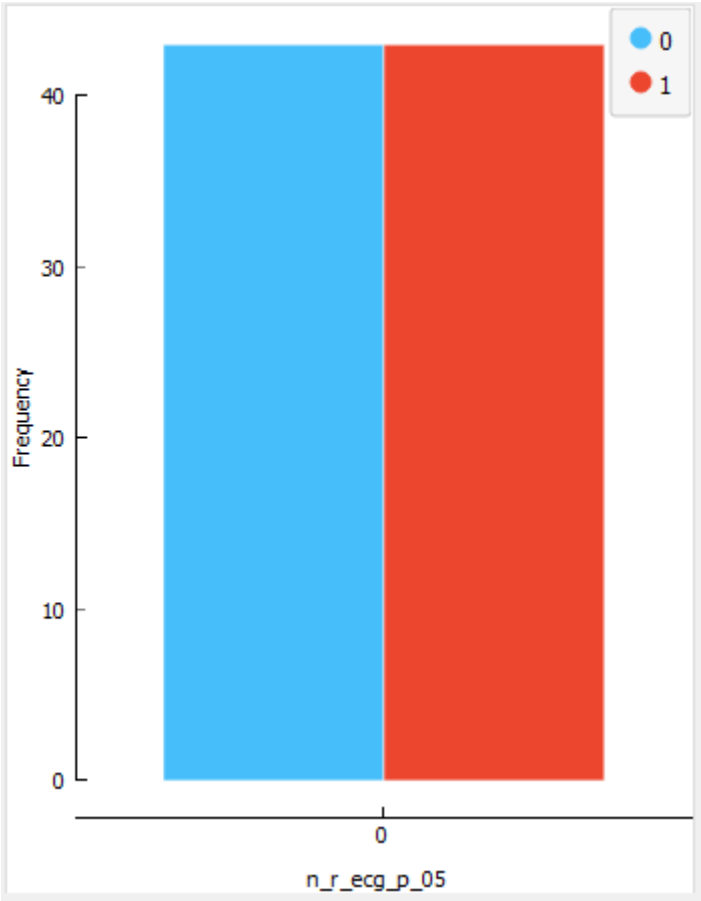

30
20
10
0
Frequency
0
1
0
0.2
0.4
0.6
0.8
1
DLIT_AG

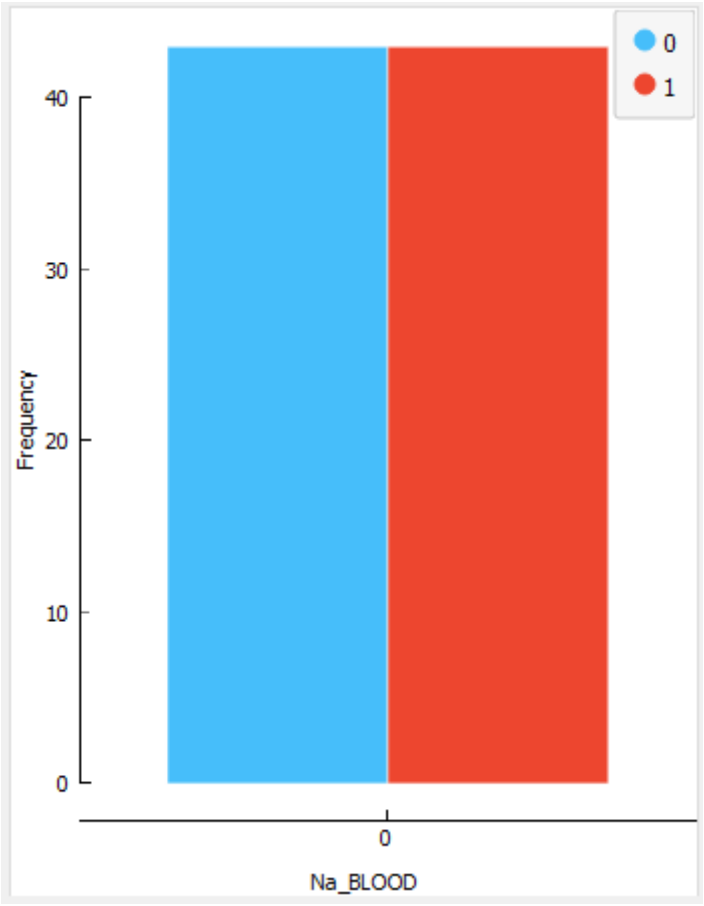

40
30
20
10
0
Frequency
0
1
0
zab_leg_04


0
1
40
30
20
10
0
Frequency
0
fibr_ter_07

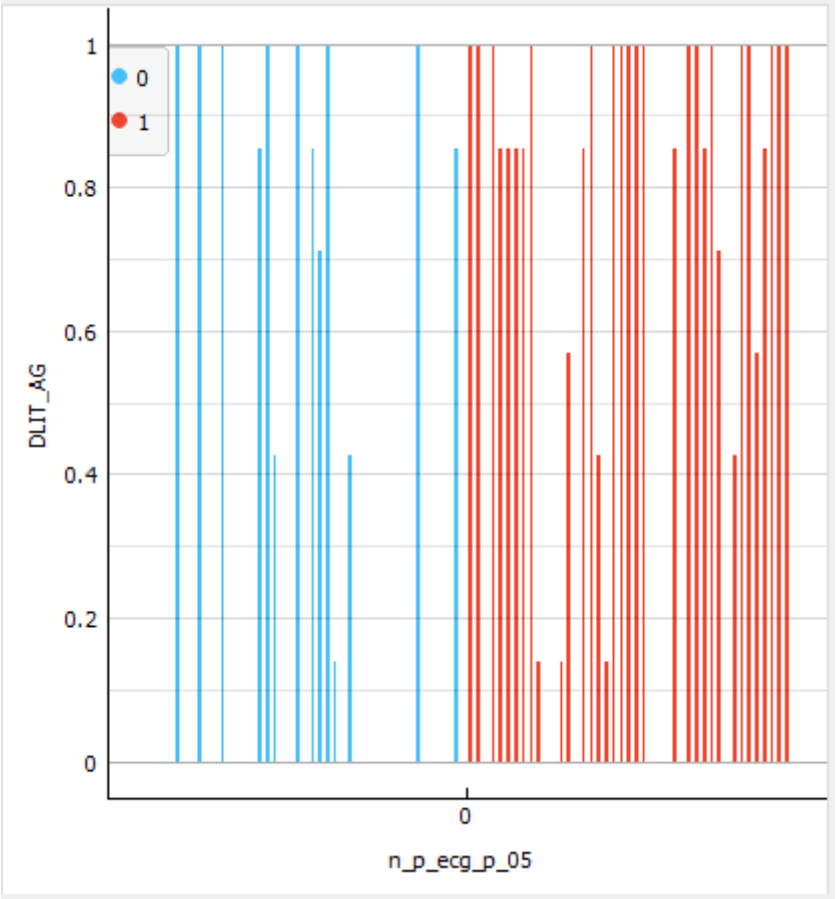

0
1
40
30
20
10
0
Frequency
0
RAZRIV


0
1
40
30
20
10
0
Frequency
0
PREDS_TAH


0
1
40
30
20
10
0
Frequency
0
n_r_ecg_p_05



- Diagramas de barras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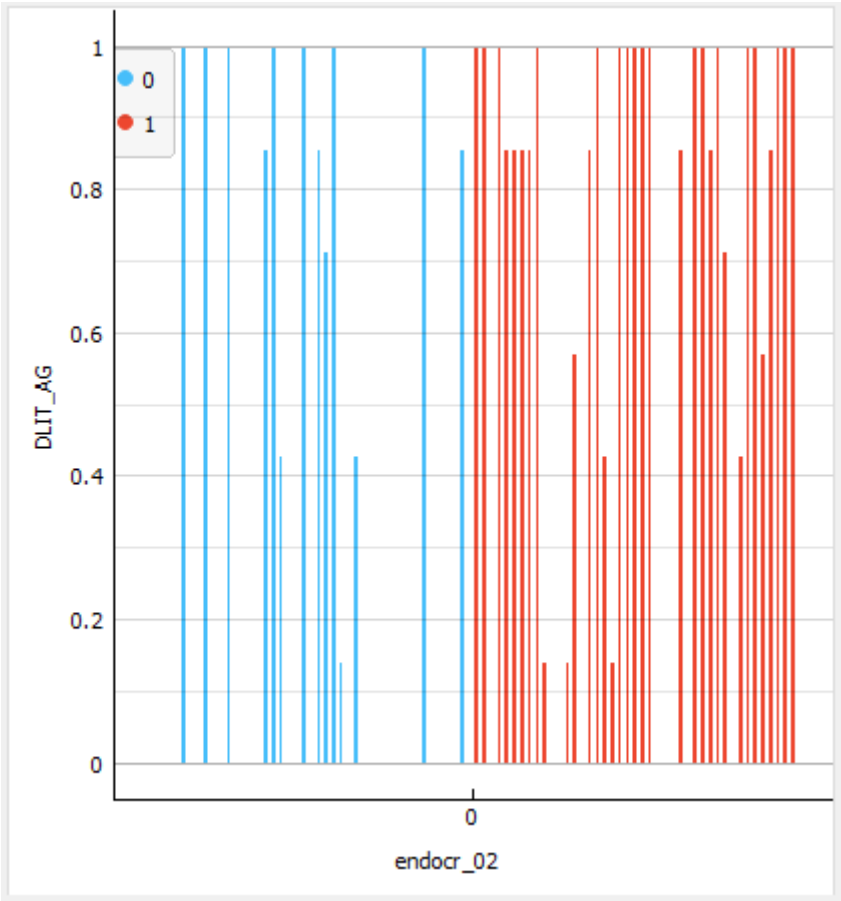
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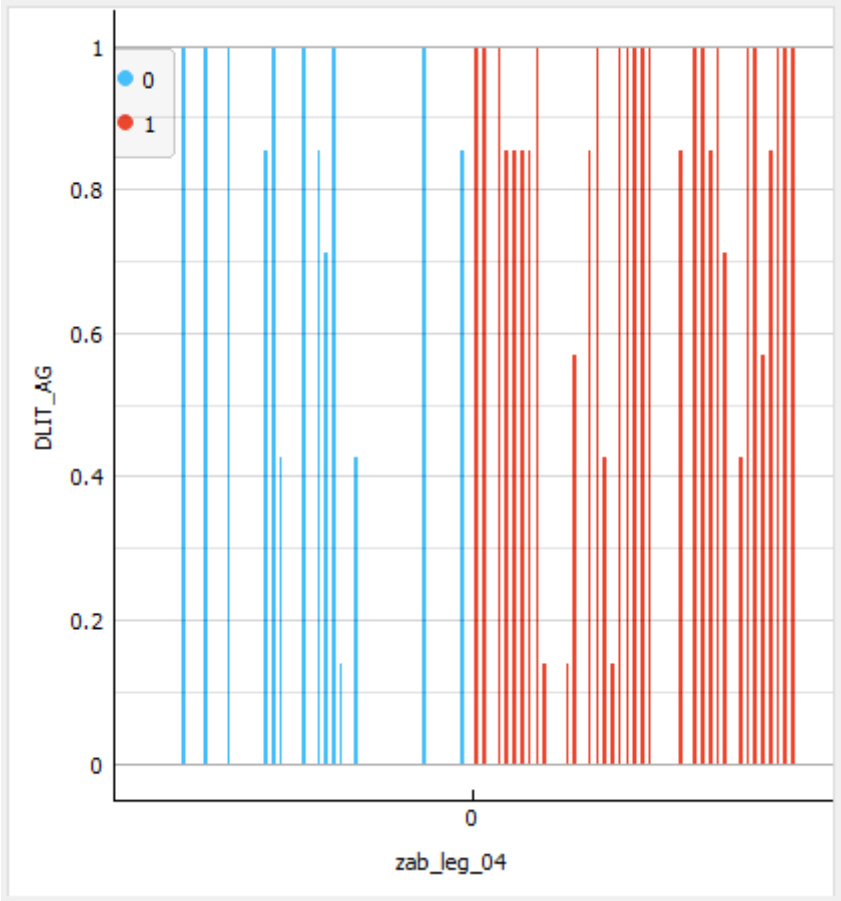
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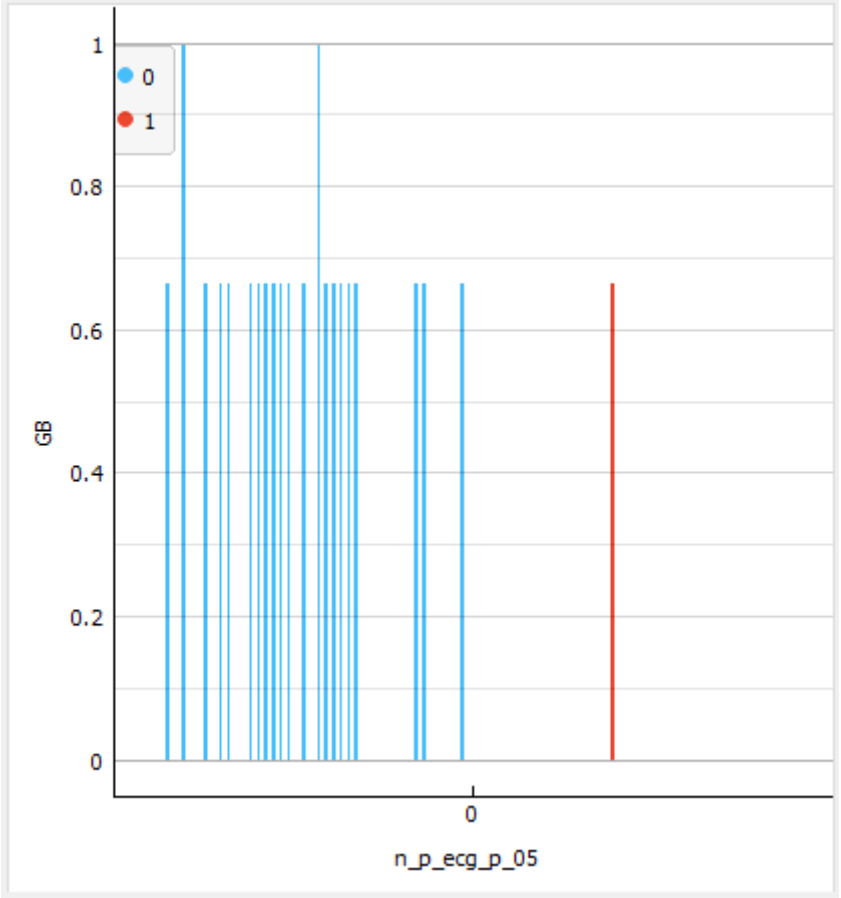
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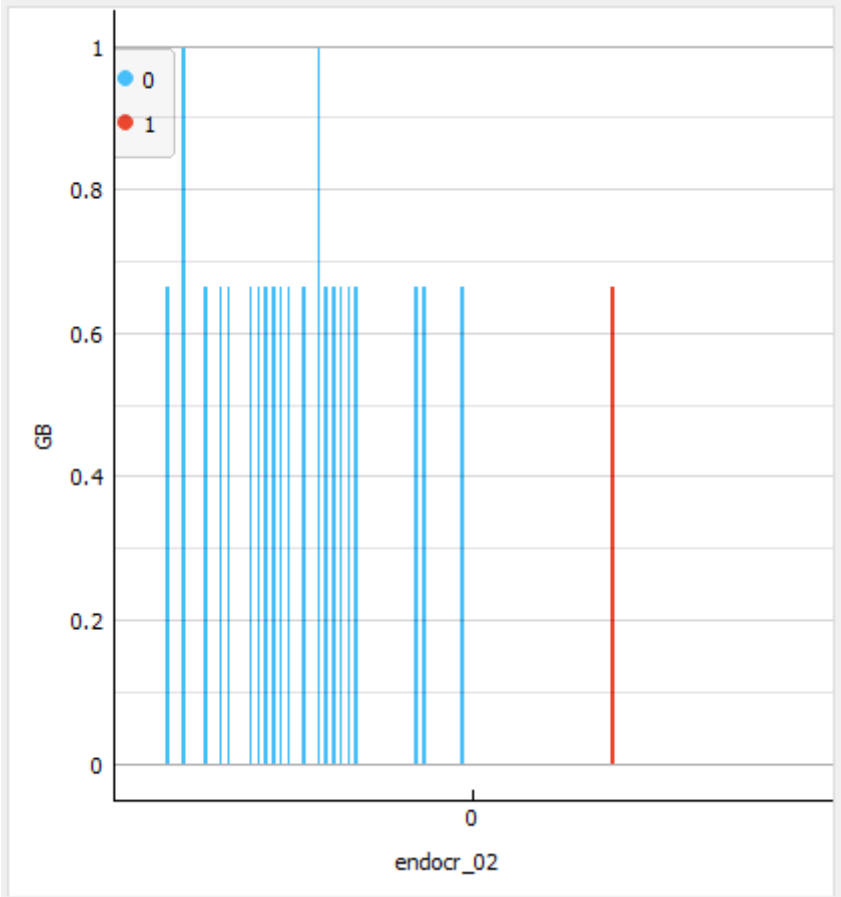
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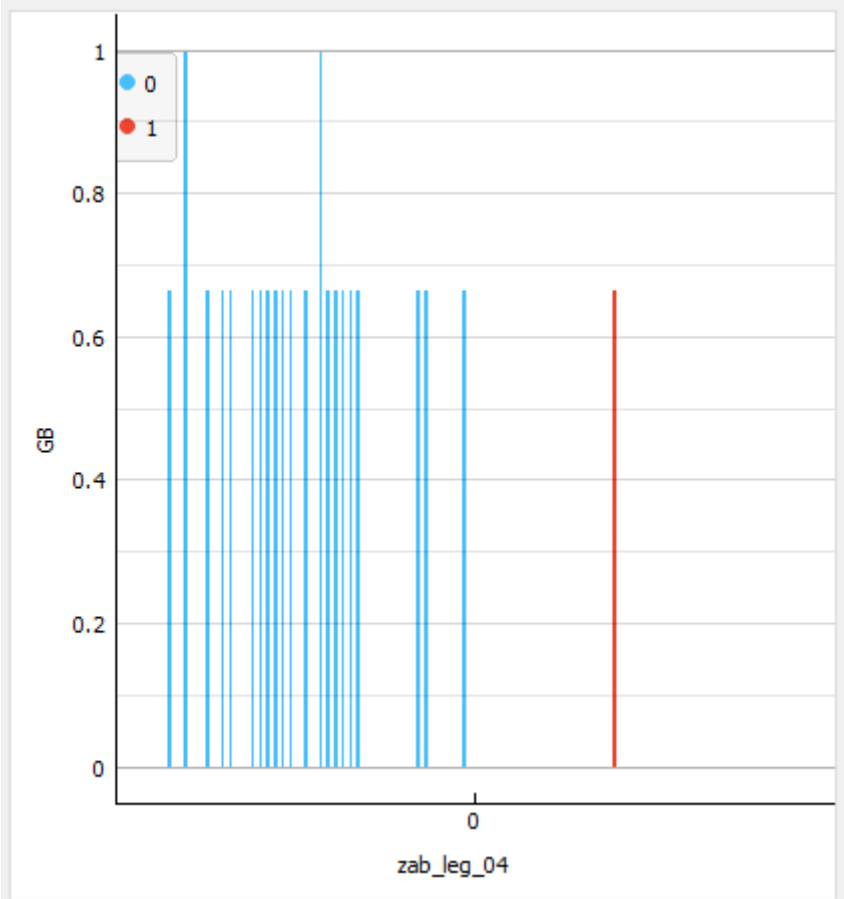
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zab_leg_04

Al igual que ocurre con los diagramas de dispersión, los diagramas de barras restantes no nos aportan información distinta de los que ya tenemos por lo que, de nuevo, no los incluimos.

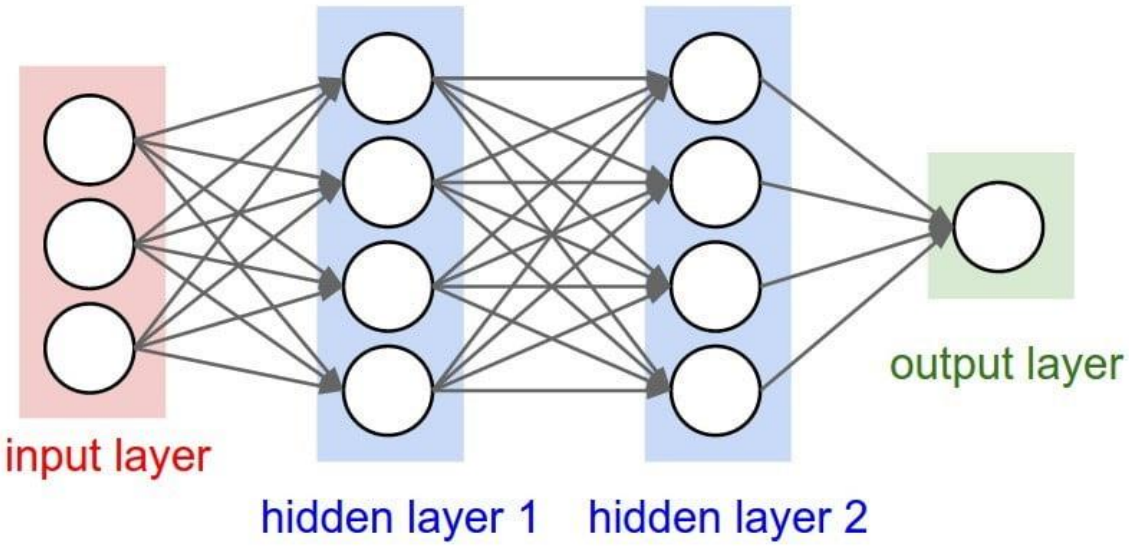
Subir el CSV preprocesado

- **Métodos (Explicar todas las técnicas utilizadas como ANOVA, Chi cuadrado, redes neuronales perceptrón multi capa con referencias en inglés)**

Para seleccionar las 10 variables más influyentes hemos utilizado el Scoring Method: *Gain Ratio*.

Para entrenar a nuestro conjunto de datos hemos utilizado un *Basic Multi_Layer Perceptron*.

- **Estructura de la red neuronal**



Nº capas de entrada: 1 capa de entrada con 10 neuronas

Nº capas ocultas: 2 capas ocultas con 15 neuronas cada una

Nº capas de salida: 1 capa de salida con 1 neurona

- **Experimentación (explicar la experimentación paso a paso)**

La experimentación en nuestro caso se ha basado en ir cambiando 4 parámetros de nuestra red neuronal y de nuestro modelo: el porcentaje de nuestro dataset que iba destinado a entrenamiento y a prueba (train-test), el número de capas ocultas, el número de neuronas que tenían nuestras capas ocultas y el número de iteraciones que realizaba nuestro modelo. Variando los 4 parámetros teníamos que encontrar la combinación de estos que más precisión diera a nuestro modelo.

Inicialmente, íbamos cambiando estos parámetros pero nos salían resultados muy dispares, incluso cuando ejecutábamos el mismo código sin cambiar nada nos daba un resultado distinto, descubrimos que se debía a la aleatoriedad con la que se dividía el dataset. Para arreglar esto introdujimos *random_state=45* en la parte del código en la que dividíamos el dataset, controlando así la aleatoriedad de la división de los datos.

Una vez hecho esto, ya podíamos ir cambiando los parámetros para comprobar que le venía mejor a nuestro modelo. Debido a que es un dataset con pocos datos, nos dimos cuenta de que tanto el número de capas ocultas como el número de iteraciones no tenía que ser muy alto. Finalmente, fuimos probando que número de neuronas por capa nos venía mejor y vimos que porcentaje de train-test nos daba más precisión. El resultado final es: 60% train – 40% test, 2 capas ocultas, 15 neuronas por capa y 2000 iteraciones.

Resultados

Matriz de confusión:

```
Confusion matrix:
[[20  0]
 [ 1 14]]
```

En la matriz de confusión resultante vemos cómo de los 35 datos destinados al test, 34 están bien clasificados (20 Verdaderos Negativos y 14 Verdaderos Positivos) y tan solo 1 dato está erróneamente clasificado, 1 Falso Negativo (El modelo predijo 0 cuando en realidad era 1). Esto indica que la precisión de nuestro modelo es realmente alta.

Precisión:

	precision	recall	f1-score	support
0	0.95	1.00	0.98	20
1	1.00	0.93	0.97	15
accuracy			0.97	35
macro avg	0.98	0.97	0.97	35
weighted avg	0.97	0.97	0.97	35

La precisión de nuestro modelo es del 97% como podemos observar, sin embargo, vista la matriz de confusión se podría esperar que fuera más alta. Esto ocurre porque nuestro dataset tiene muy pocos datos y un fallo supone mucho porcentaje de la precisión del modelo.

- **Conclusiones**

En este trabajo se ha desarrollado una red neuronal para la predicción de hipertensión sintomática (SIM_GIPERT) utilizando técnicas de minería de datos y aprendizaje automático. El preprocesamiento de los datos se realizó empleando herramientas como Orange y Weka, donde se seleccionaron las variables más relevantes mediante el método

de *Information Gain Ratio*, optimizando así el conjunto de características utilizadas en el modelo.

Posteriormente, se construyó una red neuronal tipo multitask utilizando *MLPClassifier* de *Scikit-learn*, configurada con dos capas ocultas de 15 neuronas cada una. El modelo fue entrenado sobre el dataset preprocesado, alcanzando un accuracy del 97% en el conjunto de prueba, lo que demuestra una alta capacidad de predicción.

Estos resultados reflejan la eficacia de combinar un adecuado preprocesamiento de los datos, una correcta selección de atributos y un diseño cuidado del modelo de red neuronal. Además, resaltan el potencial del uso de inteligencia artificial en el ámbito clínico como apoyo en el diagnóstico temprano de condiciones como la hipertensión.

- **Referencias (IEEE y mínimo 10 referencias)**

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