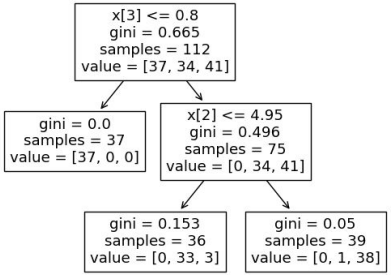
Paradigma

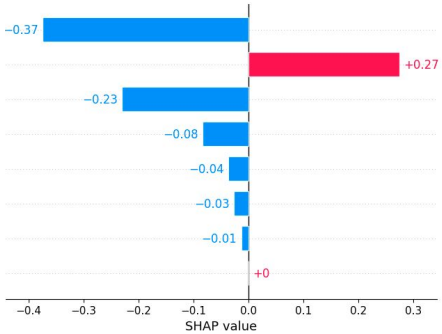
Explicabilidad local, ¿cómo interpreto la predicción?

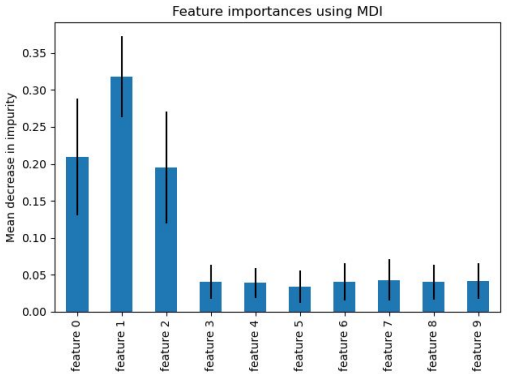
A ver qué es esto de la explicabilidad.

Modelos explicables.

Construidos para ser interpretados.

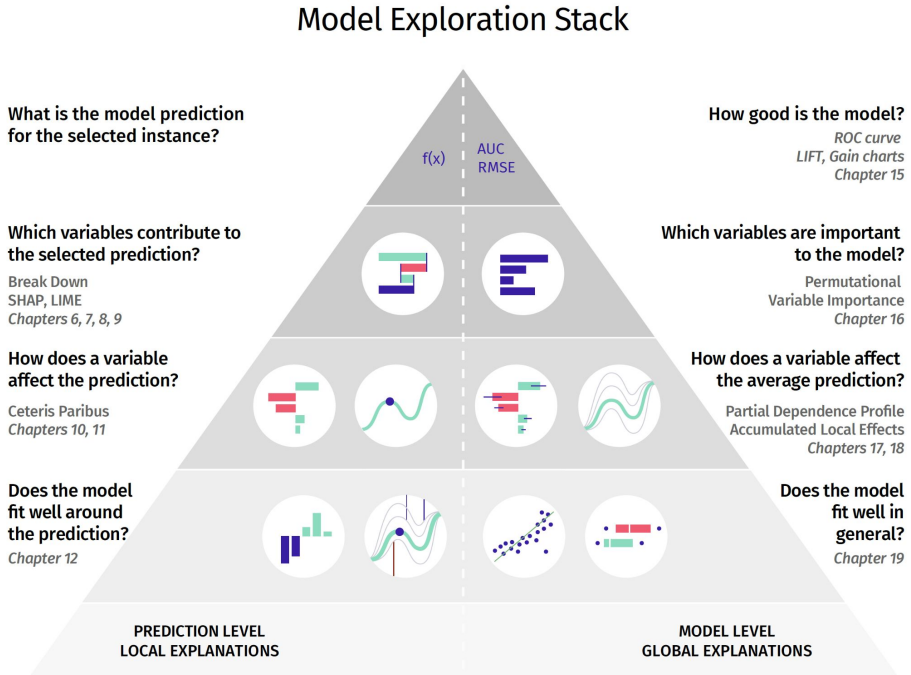






Modelos explicables.

Expli-qué.



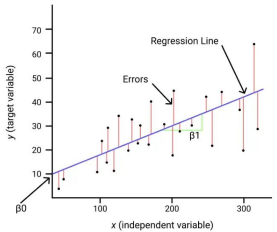
Explanatory Model Analysis

El abanico de posibilidades.

Caja blanca.

P. ej:

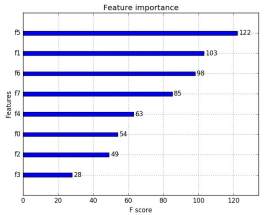
Generalised Linear Models



Explicable globalmente.

P. ej:

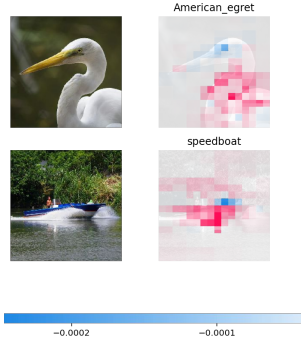
XGBoost



Explicable post-hoc.

P. ej:

Neural Networks



Be SHAP, my friend.

SHapley Additive exPlanations.

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'_i,$$

where $z' \in \{0,1\}^M$, *M is the number of simplified input features, and* $\phi_i \in \mathbb{R}$.

01 — Basados en Teoría de juegos colaborativa.

02 — **Aditivos**

03 — Local accuracy

04 — Missingness

05 — Consistency

SHAP

Epidemiologic Follow Up Study (NHEFS).

Personas entre 25-74 años de edad que han completado el examen médico NHANES I

	Non-Null Count	Dtype
sex_isFemale	14264	bool
age	14264	int64
physical_activity	14264	int64
...	...	...
creatinine_isUnacceptable	14264	bool
bmi	14264	float64

explainer.

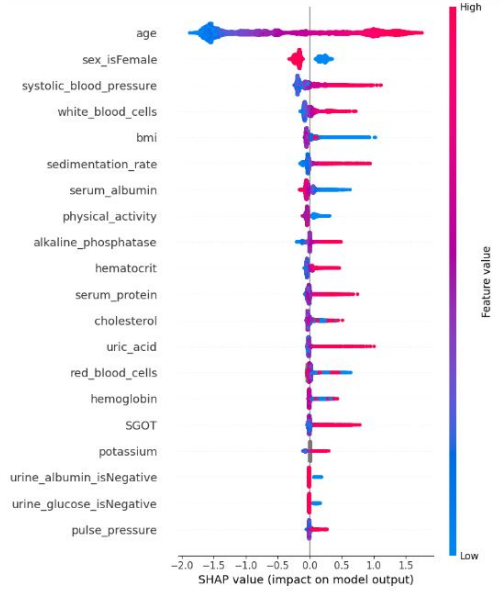
```
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(X)
explanations = explainer(X)
```

```
--Explainer dataframe--
.values =
array([[ 1.84628233e-01, -5.04557610e-01, -3.13231274e-02, ...,
        -1.92297876e-01, -1.64051000e-02, -5.78483492e-02],
       [ 1.66194662e-01, -1.09421897e+00,  5.98950498e-02, ...,
         -2.91730892e-02, -6.48942171e-03, -4.91099022e-02],
       [-1.49643376e-01, -1.56533003e+00,  7.20566958e-02, ...,
         -1.84312284e-01,  3.18674967e-02, -3.89468074e-02],
       ...,
       [-2.05180049e-01, -9.24388349e-01,  6.81497306e-02, ...,
         -2.10007086e-01,  2.53346898e-02,  3.22342068e-01],
       [-2.38794148e-01,  3.31081092e-01, -2.36861296e-02, ...,
          2.89917737e-01, -2.62622605e-04, -6.56308085e-02],
       [ 1.60021782e-01, -1.59773672e+00, -2.64430381e-02, ...,
          1.45278588e-01, -1.00701945e-02,  1.04265157e-02]], dtype=float32)

.base_values =
array([-0.6702478, -0.6702478, -0.6702478, ..., -0.6702478, -0.6702478,
       -0.6702478], dtype=float32)

.data =
array([[False, 51, 3, ..., 110.0, 40.0, 25.406802871255213],
       [False, 41, 2, ..., 136.0, 54.0, 24.58833108784943],
       [True, 31, 2, ..., 110.0, 24.0, 23.75650236105149],
       ...,
       [True, 47, 2, ..., 108.0, 28.0, 17.91519880435943],
       [True, 61, 8, ..., 180.0, 68.0, 27.33162170820975],
       [False, 29, 3, ..., 152.0, 60.0, 33.16143518222725]], dtype=object)
<class 'shap._explanation.Explanation'>
```

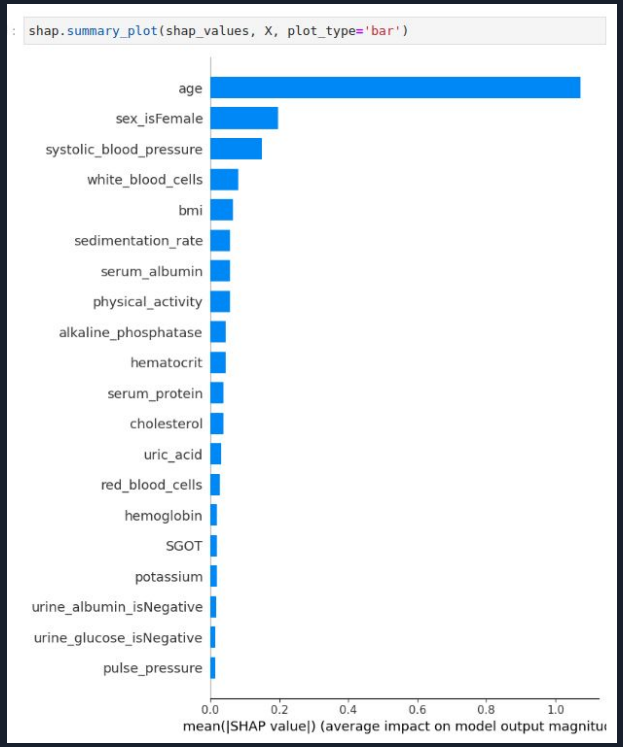
El objeto principal de SHAP

```
shap.summary_plot(shap_values, X)
```

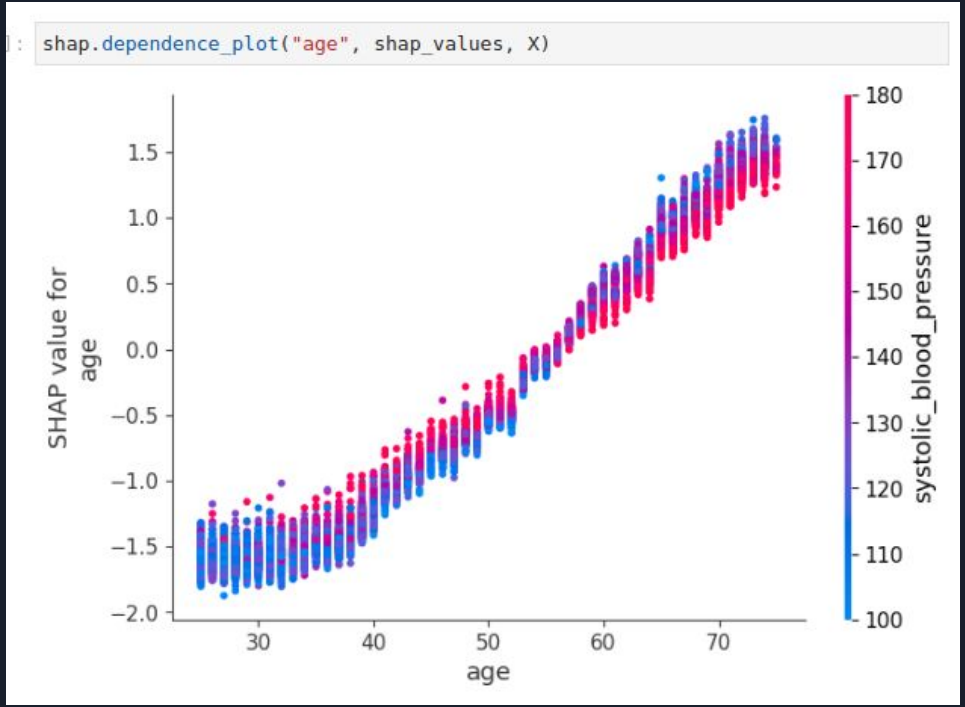
```
/home/bhernandez/Documents/pydata2023/venv/lib/python3.8/site-packag
es/shap/plots/_beeswarm.py:664: UserWarning:

No data for colormapping provided via 'c'. Parameters 'vmin', 'vmax'
will be ignored
```



Contribución total.

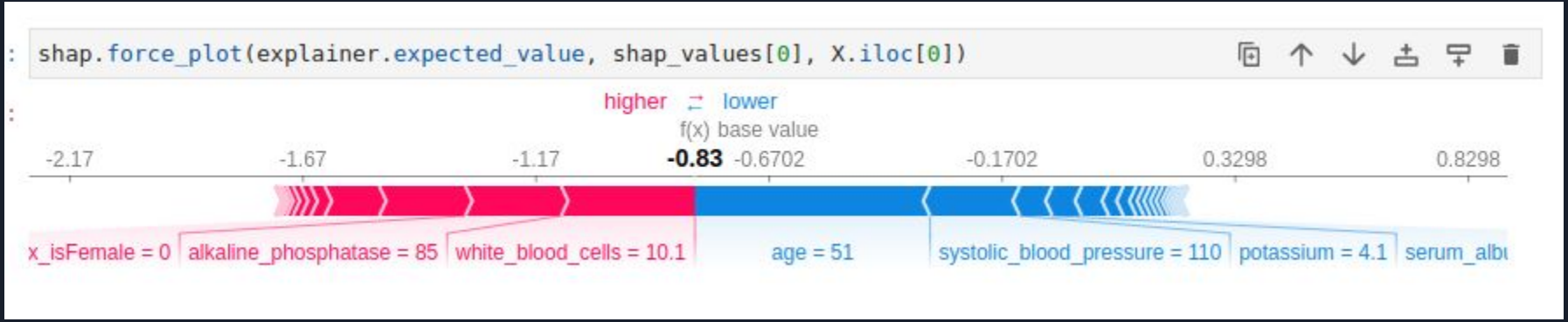


Contribución parcial.

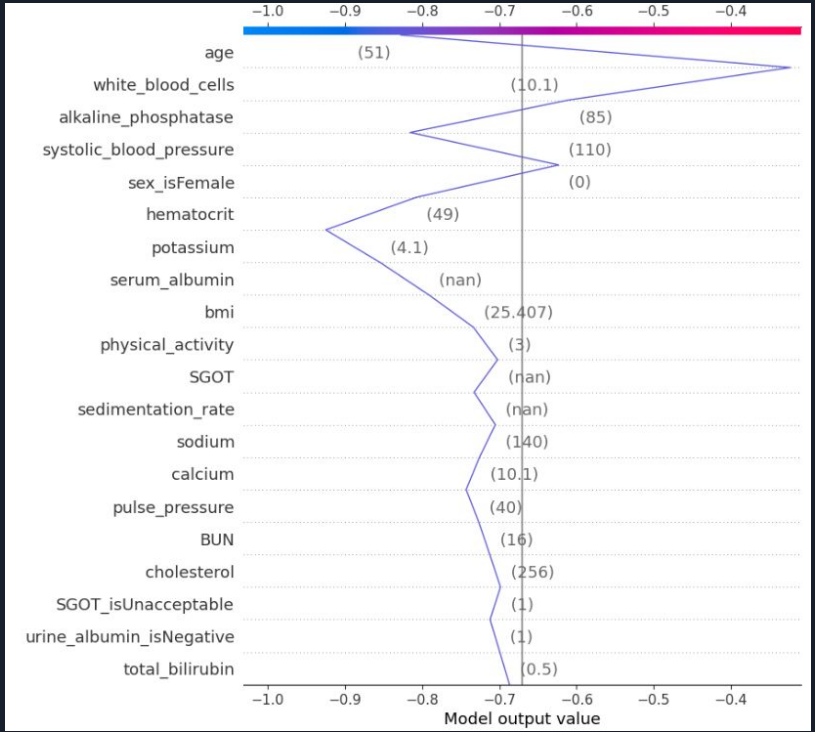


Concretando.

Explicabilidad local.



Explicabilidad local.

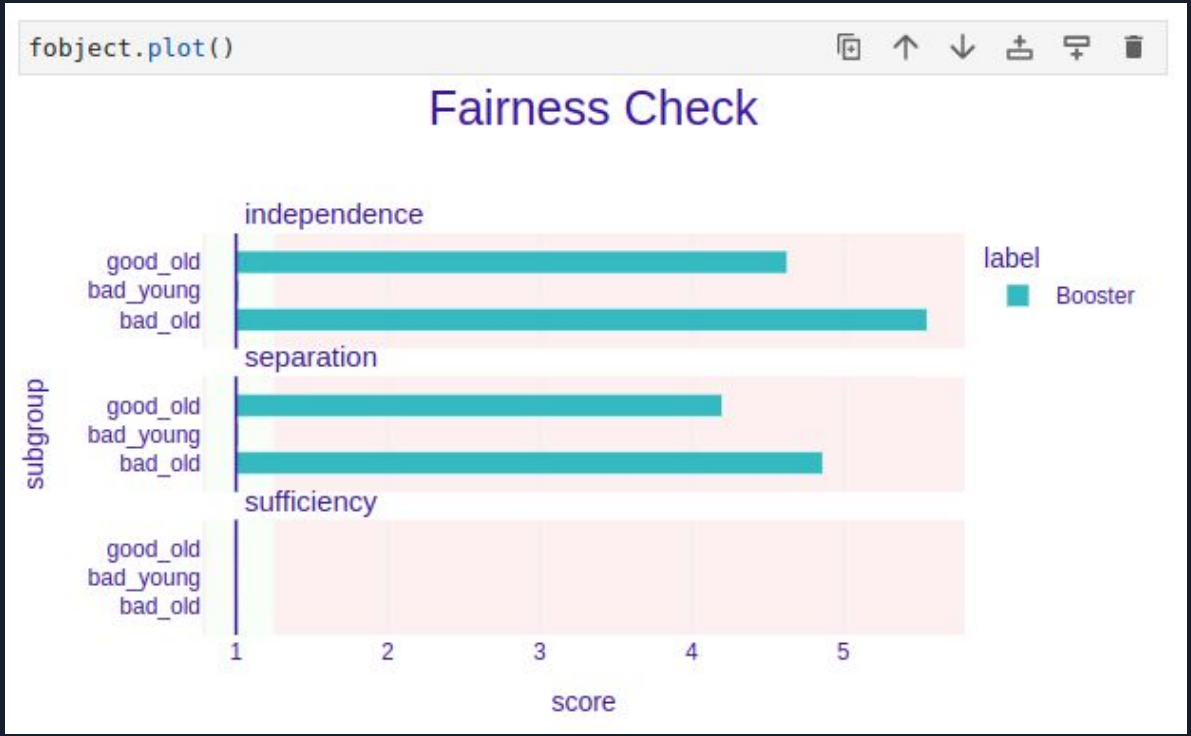


D ALEX.

dEscriptive mAchine Learning EXplanations.

$$\forall_{i \in \{a,b,\ldots,z\}} \epsilon < \frac{metric_i}{metric_{privileged}} < \frac{1}{\epsilon}$$

fairness.



Fairness and machine learning

¡Muchas gracias!