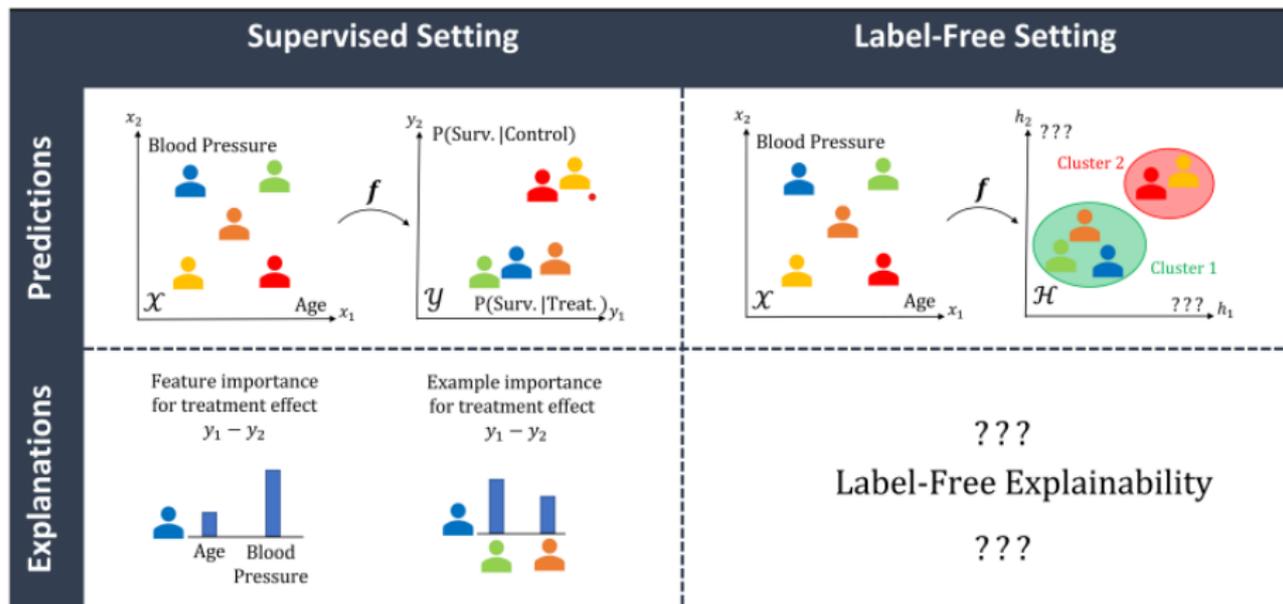


Label free explainability for Unsupervised Model

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Label-Free Explainability



Label-free Importance

1 Feature Importance



2 Example Importance



- Feature Importance With Labels.

$$b_i(\mathbf{f}, \mathbf{x}) \equiv \sum_{j=1}^{d_y} f_j(\mathbf{x}) \cdot a_i(f_j, \mathbf{x}).$$

- Feature Importance With Label-Free

$$b_i(\mathbf{f}, \mathbf{x}) \equiv a_i(g_{\mathbf{x}}, \mathbf{x})$$

$g_{\mathbf{x}} : \mathcal{X} \rightarrow \mathbb{R}$ such that for all $\tilde{\mathbf{x}} \in \mathcal{X}$:

$$g_{\mathbf{x}}(\tilde{\mathbf{x}}) = \langle \mathbf{f}(\mathbf{x}), \mathbf{f}(\tilde{\mathbf{x}}) \rangle_{\mathcal{H}},$$

- Label-Free Completeness.

$$\sum_{i=1}^{d_X} b_i(\mathbf{f}, \mathbf{x}) = \|\mathbf{f}(\mathbf{x})\|_{\mathcal{H}}^2 - b_0.$$

Label-free importance scores = sum to the black-box norm

- Loss-Based Example Importance

(Supervised setting)

In a supervised setting, this typically correspond to a couple $z = (x, y)$ with an input $x \in X$ and a label $y \in Y$.

$$\delta_{\theta}^n L(z, \theta_*) \equiv L(z, \theta_*^{-n}) - L(z, \theta_*).$$

- Loss-Based Example Importance

(Label-free setting)

Is it enough to drop the label and fix $z = x$ in all the above expressions? No. -> Loss function can be different!

- Representation-Based Example Importance

(Supervised setting)

$$\mathbf{f}_l \circ \mathbf{f}_e : \mathcal{X} \rightarrow \mathcal{Y}, \quad \begin{array}{ll} \mathbf{f}_e : \mathcal{X} \rightarrow \mathcal{H} & \text{Inputs} \rightarrow \text{representations} \\ \mathbf{f}_l : \mathcal{H} \rightarrow \mathcal{Y} & \text{representations} \rightarrow \text{labels} \end{array}$$

$$\mathbf{f}_e(\mathcal{D}_{\text{train}}): \mathbf{f}_e(\mathbf{x}) \approx \sum_{n=1}^N w^n(\mathbf{x}) \cdot \mathbf{f}_e(\mathbf{x}^n).$$

$$w^n(\mathbf{x}) = \mathbf{1}[n \in \text{KNN}(\mathbf{x})] \cdot \kappa[\mathbf{f}_e(\mathbf{x}^n), \mathbf{f}_e(\mathbf{x})]$$