

Math 342 Lecture 3

$$y = g(\vec{x}) + \underbrace{[h^*(\vec{x}) - g(\vec{x})] + [f(\vec{x}) - h^*(\vec{x})] + [t(\vec{x}) - f(\vec{x})]}_{\text{"e" = residual}}$$

$\hat{y} \approx \text{model}$

lec 2 recap

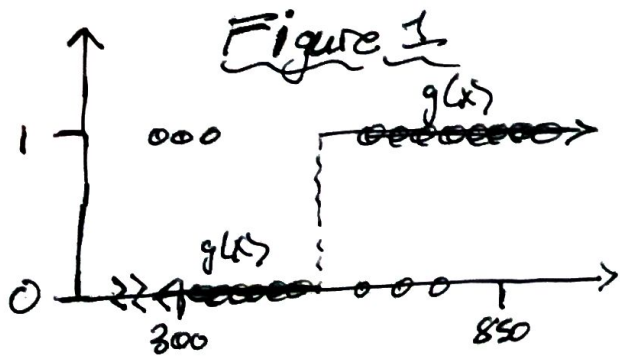
$$g = \mathcal{R}(\mathcal{D}, \mathcal{H}) \in \mathcal{H}$$

$$y = \{0, 1\}^n \Rightarrow \text{payback loan}$$

$$x = [\vec{x}, 1] ; \vec{x} \in [300, 850]^n \Rightarrow \text{Credit Scores}$$

$$\mathcal{D} \Rightarrow [\vec{x} | \vec{y}] = \begin{bmatrix} 810 & 1 \\ 300 & 0 \\ \vdots & \vdots \end{bmatrix} \Rightarrow \mathcal{D}$$

Data frame



Binary Classification, g returns either a 0 or 1 in the output space

$$\mathcal{H} = \{ \mathbb{I}_{x \geq \theta} : \theta \in \mathcal{X} \}$$

Null Model

$$g_0 = \mathcal{R}(\vec{y}, \mathcal{H}) = \text{Mode}(\vec{y}) \text{ for classification}$$

\hookrightarrow no features

Indicator Function
1: if cond.
0: if not

Continuing from Figure 1

We are aiming to choose a threshold line, such that we minimize the residuals

$$y_0 \begin{matrix} 0 & 0 \\ 1 & 1 \end{matrix} \hat{y}_1 \begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \Rightarrow e \Rightarrow \frac{1}{n} \sum_{i=1}^n |e_i| = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{y_i \neq \hat{y}_i} \Rightarrow \text{Misclassification Error (ME)}$$

Accuracy = $1 - ME$
 \rightarrow Our algorithm
 \mathcal{A} : Minimize ME
 \hookrightarrow Objective Function
 \hookrightarrow Fitness Function
 \hookrightarrow Target Function

\mathcal{A} returns Θ_g s.t. ...

$$\Theta_g = \arg \min_{\Theta \in \Phi} \left\{ \sum_{i=1}^n \mathbb{1}_{\underbrace{y_i \geq \Theta}_{\hat{y}_i} \neq y_i} \right\}$$

\nwarrow
unique values of \vec{x}_1

$$\frac{1}{n} \sum_{i=1}^n |e_i|$$

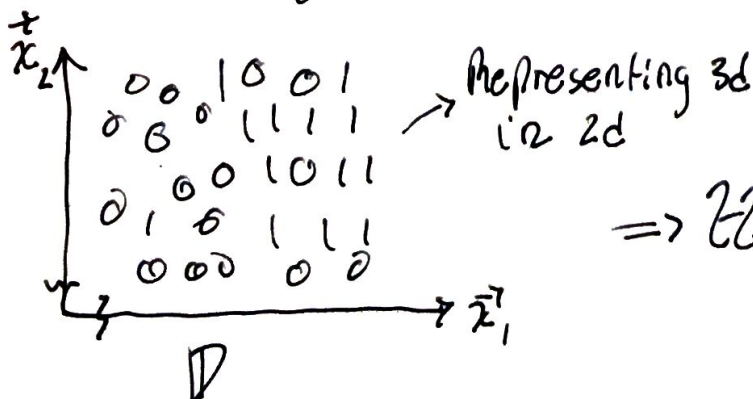
SAE: Sum Absolute Error

MAE: Mean Absolute Error

MSE: Mean Squared Error $|e_i| \rightarrow e_i^2$

NOTE

Now we add a new feature \vec{x}_2



$$\Rightarrow \mathcal{H} = \{ \mathbb{1}_{x_1 \geq \theta_1}, \mathbb{1}_{x_2 \geq \theta_2} : \theta_1, \theta_2 \in \mathbb{R} \}$$