

11-OCT-2025

Agenda:

Logistic Regression

Implementation of LR

ROC, AUC

Cross-validation

logistic regression: $y = mx + c$
→ classification
Activation fn / logistic function → sigmoid → input range
→ $-\infty$ to ∞
→ output range → 0 to 1

$z = mx + c \rightarrow \text{sigmoid} \rightarrow \begin{matrix} 0 \\ 1 \end{matrix} \int \text{threshold} > 0.5 \rightarrow \begin{matrix} 0 \\ 1 \end{matrix}$

$$z = mx + c$$

height \rightarrow short $\rightarrow 0$
 \rightarrow tall $\rightarrow 1$ } binary

sigmoid(z) $\rightarrow \hat{y} \rightarrow$ prob \rightarrow 0.2 \rightarrow prob of tall is 20%.
 \rightarrow 0.8 \rightarrow prob of tall is 80%.

Linear regression:

$$\begin{matrix} y = 80 \\ \hat{y} = 91 \end{matrix} \left. \vphantom{\begin{matrix} y = 80 \\ \hat{y} = 91 \end{matrix}} \right\} \text{mse} \rightarrow (y - \hat{y})^2$$

Logistic regression:

$$\begin{matrix} z = 80 \\ \text{sigmoid}(z) \rightarrow 0.8 \end{matrix} \leftarrow \hat{y} \begin{matrix} 0-1 \\ \downarrow \\ 0 \end{matrix} \left. \vphantom{\begin{matrix} z = 80 \\ \text{sigmoid}(z) \rightarrow 0.8 \end{matrix}} \right\} \text{mse will not work}$$

To solve this prob, we need a different cost function.

Modified MSE (Linear Regression)

$$\frac{1}{2m} \sum_{i=1}^m (y_i - \hat{y}_i)^2$$

logistic Regression:

$$\begin{aligned} J(\beta) &= -\frac{1}{m} \sum_{i=1}^m (y_i \cdot \log(\hat{y}_i) + (1-y_i) \cdot \log(1-\hat{y}_i)) \\ \text{cost function} &= \end{aligned}$$

$$m=1, y=0, y_{\text{pred}}=0.9 \quad (\text{case 1})$$

$$\begin{aligned} &= - (y_i \cdot \log(\hat{y}_i) + (1-y_i) \cdot \log(1-\hat{y}_i)) \\ &= - [0 \cdot \log(0.9) + (1-0) \cdot \log(1-0.9)] \\ &= - [0 + 1 \cdot \log(0.1)] \\ &= - \log(0.1) \\ &= - (-2.3025) \\ &= 2.3025 \end{aligned}$$

$$\text{MSE} = 0.81$$

$$m=1, y=0, y_{\text{pred}}=0.1 \quad (\text{case 1})$$

$$\begin{aligned} &= - [0 \cdot \log(0.1) + (1-0) \cdot \log(1-0.1)] \\ &= - [0 + 1 \cdot \log(0.9)] \\ &= - \log(0.9) \\ &= - (-0.10536) \\ &= 0.10536 \end{aligned}$$

case 1 ($y=0, y\text{-pred}=0.9$) : cost ≈ 2.3025 (high cost)
case 2 ($y=0, y\text{-pred}=0.1$) : cost ≈ 0.10536 (low cost)

Flow of logistic regression.

- 1) $x_1, x_2, x_3, x_4 \rightarrow$ linear equation for intermediate $o/p \rightarrow z$
- 2) $z \rightarrow$ sigmoid $\rightarrow \hat{y}$
- 3) loss-function gradient ($y, y\text{-pred}$) \rightarrow update weight/parameters.
- 4) calculate final loss using loss/cost function. \downarrow
 m, β
- 5) Iterate until satisfied \downarrow
learnable parameters
- 6) Done

Out of context topic.

Data card:

- \rightarrow info about data
- \rightarrow sources
- \rightarrow rows & columns
- \rightarrow features \rightarrow info \rightarrow range of each feature, type
- \rightarrow Missing values

Model card:

- \rightarrow performance
- \rightarrow link of test set on which we did evaluation
- \rightarrow sklearn
- \rightarrow confusion matrix
- \rightarrow date

imputation = [1, 2, 3, 4, 6]

numerical = [1, 2, 3, 4, 5, 6]

transformer = [] → object of sklearn pipeline

if imputation:

① pipeline → imputation on imputation list
→ scaling on imputation list

append ① to transformer list

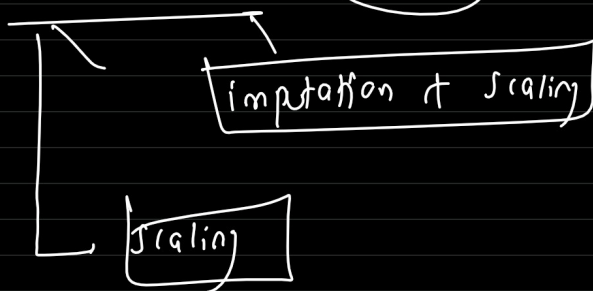
② [if numerical is not present] → [5]

pipeline → scaling → [5]

else:

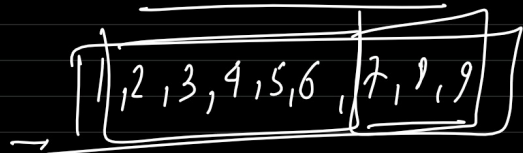
pipeline → scaling → [numerical (id)]

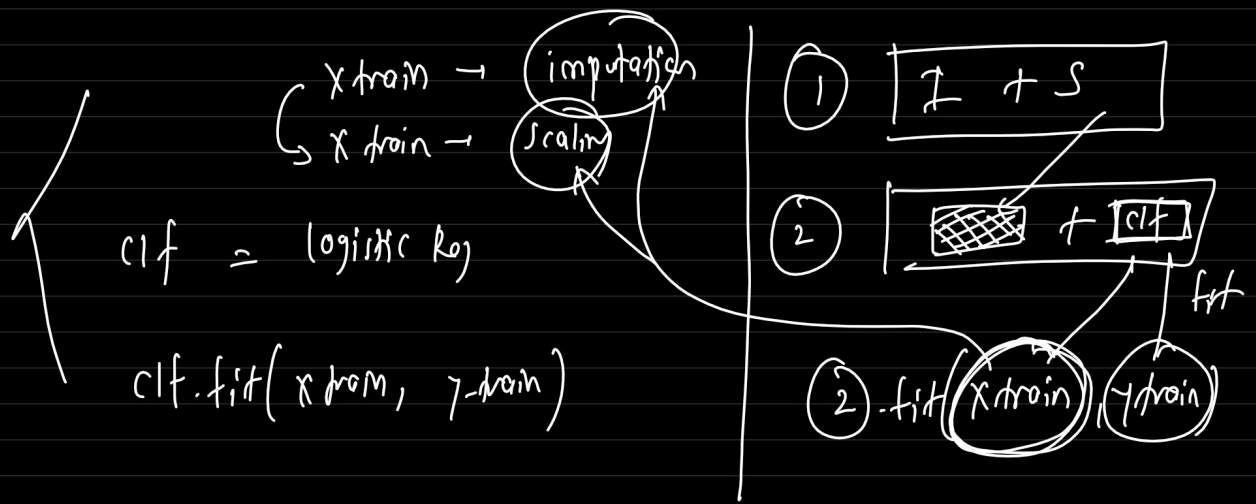
1, 2, 3, 4, 5, 6, 7, 8, 9 remainder = "drop")



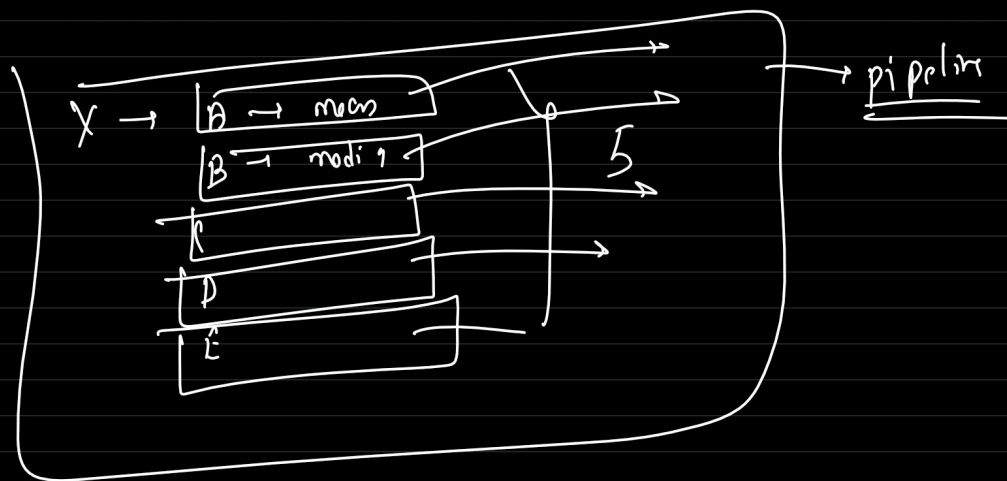
transform()

remainder = "passthrough"





first
problem



predict

$$z = x_{train} \cdot \text{dot}(\text{weights}) + \text{bias}$$

$$p = \text{sigmoid}(z)$$

$$\hat{y} = (p \geq 0.5) \text{ I else } 0$$