

Performance Metrics

Performance Metrics in logistic Regression

Performance metrics in logistic regression are used to evaluate the effectiveness and accuracy of the model in predicting categorical outcomes. Logistic regression is commonly used for binary classification problems, where the outcome variable is binary (e.g., yes/no, 1/0).

Confusion Matrix



$2 \times 2 \rightarrow \text{Matrix}$

$2 \rightarrow \text{Rows}$

$2 \rightarrow \text{Columns}$

Actual

→

1 0

1	3
1	1

Pre

1

0

Dataset

x_1

x_2

Actual

y

Predicted

$\hat{y} \leftarrow \text{Model predict}$

1 \leftarrow Wrong

1 → Correct

0 → Correct

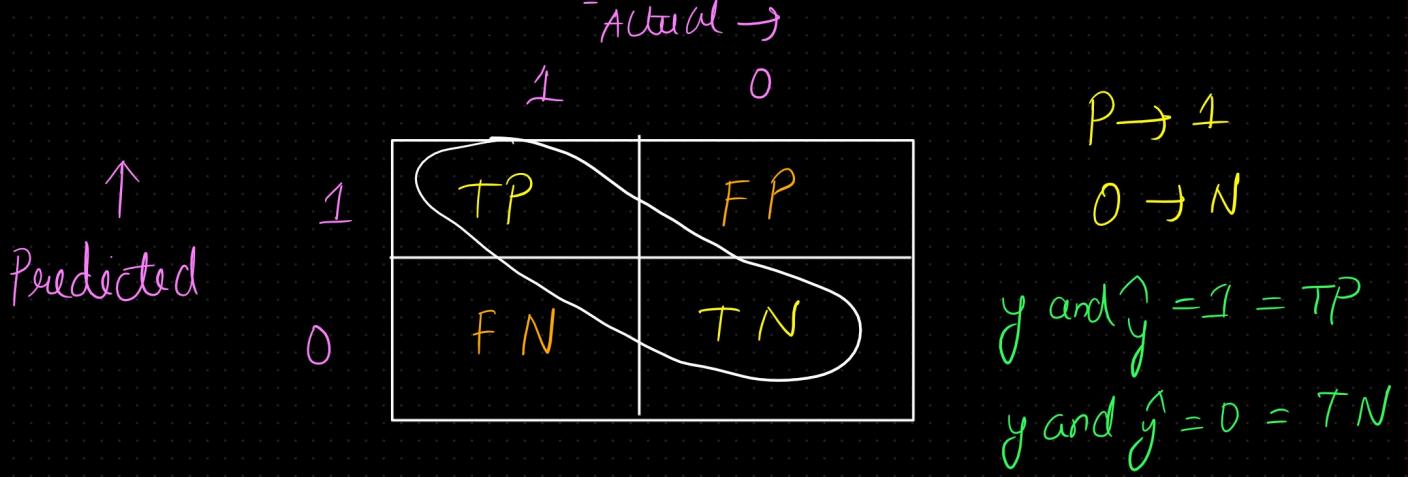
1 → 11

1 → Correct

1 → Wrong

0 → Wrong

-	-	0	1	1 → Correct
-	-	0	1	0 → Correct
-	-	1	1	1 → 11
-	-	1	0	1 → Correct
-	-	0	1	1 → Wrong
-	-	1	0	0 → Wrong



Confusion metrics, often presented in the form of a confusion matrix, are used to evaluate the performance of classification models, including logistic regression. A confusion matrix is a table that summarizes the performance of a classification algorithm by tabulating the actual and predicted class labels. It helps to visualize the model's performance in terms of true positives, true negatives, false positives, and false negatives

True Positive (TP): The number of instances where the model correctly predicts the positive class.

True Negative (TN): The number of instances where the model correctly predicts the negative class.

False Positive (FP): Also known as Type I error, the number of instances where the model incorrectly predicts the positive class (false alarm).

False Negative (FN): Also known as Type II error, the number of instances where the model incorrectly predicts the negative class (miss).

① Accuracy

$$\text{Model Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

The proportion of correctly classified instances out of the total number of instances

$$= \frac{3+1}{7} = \frac{4}{7} = 0.57 = 57\%$$

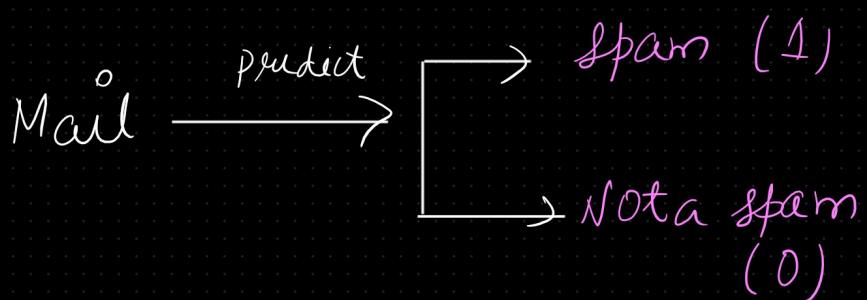
Imbalanced Dataset

1000 datapoint → $\begin{cases} 900 \rightarrow 1 \\ 100 \rightarrow 0 \end{cases}$

Imbalanced dataset

② Precision

	$\frac{TP}{TP + FP}$	}
1	0	
1	TP	Email Model
0	FN	spam classification
TN	FP	



① Mail \rightarrow spam } good
 Model \rightarrow spam } scenario

② 1 \leftarrow Mail \rightarrow spam } FN
 0 \leftarrow Model \rightarrow Not a spam }

③ Mail → Not a spam }
Model → spam } Blunder

FP is important
FP ↓ ↓ → avoid, Reduce

Precision Performance Metrics

The proportion of true positive predictions out of all positive predictions made by the model. It measures the model's ability to avoid false positives.

$$P = \frac{TP}{TP + FP}$$

Out of all the actual values how many are correctly predicted

③ Recall

$$\frac{TP}{TP + FN} \Rightarrow FN \downarrow \downarrow$$

Out of all predicted values how many are correctly predicted with actual values

We care

=

FN is Important

→ To predict whether a person has
a diabetes or not

Actual
→

		Diabetes	No Diabetes
predicted ↑	Diabetes	TP	FP
	No Diabetes	FN	TN

① Actual → Diabetes } Good
Model → Diabetes }

$FN \downarrow$

② Actual → Diabetes } Blunder
Model → No Diabetes }

③ Actual → No Diabetes } $FP = \text{Wrong}$
Model → Diabetes } predict

The proportion of true positive predictions out of all actual positive instances in the dataset. It measures the model's ability to capture positive instances.

$$R = \frac{TP}{TP + FN}$$

(4) F - Beta score

$$= (1 + \beta^2) * \frac{P * R}{P + R}$$

* F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall and is particularly useful when the class distribution is imbalanced.

Case I

If FP and FN are both important

$$\beta = 1 \quad \text{Harmonic mean} \rightarrow$$

$$\boxed{F1 \text{ Score} = 2 * \frac{P * R}{P + R}}$$

② If FP is more than FN

$$\beta = 0.5$$

$$F0.5 \text{ Score} = (1 + 0.25) \frac{P * R}{P + R}$$

③ If FN is more important than FP
 $FN \gg FP$
 $\beta = 2$

$$F2_{S_{COOL}} = (1+4) \frac{P * R}{P + R}$$