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

↓

2x2 → Matrix

2 → rows

2 → columns

Actual →

		1	0
Pre	1	3	2
	0	1	1

Dataset

x_1	x_2	Actual y	Predicted $\hat{y}$ ← Model predict	
_	_	0	1	← Wrong
_	_	1	1	→ Correct
_	_	0	0	→ Correct
_	_	1	1	→ "
_	_	1	1	→ Correct
_	_	0	1	→ wrong
_	_	1	0	→ wrong

		Actual → 1	0
↑ Predicted	1	TP	FP
	0	FN	TN

$P \to 1$

$0 \to N$

y and $\hat{y} = 1 = TP$

y and $\hat{y} = 0 = TN$

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

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

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 → 900 → 1, 100 → 0

⇒

Imbalanced dataset

② Precision

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

Email
↓ Model
Spam Classification

	1	0
1	$\boxed{TP}$	FP
0	FN	TN

Mail $\xrightarrow{\text{predict}}$ Spam (1) / Not a spam (0)

① Mail → spam
Model → spam } Good scenario

② 1 ← Mail → spam
0 ← Model → Not a spam } FN

(2) 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.

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

} out of all the actual values how many are correctly predicted

(3) Recall

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

⇒ FN ↓↓

out of all predicted values how many are correctly predicted with actual values usecase

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
Model → Diabetes } Good

② Actual → Diabetes
Model → No Diabetes } Blunder

FN ↓↓

③ Actual → No Diabetes
Model → Diabetes } FP = wrong 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

$\beta = 1$

Harmonic mean

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

(2) If FP is more than FN

$\beta = 0.5$

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

③ If FN is more important than FP

$$FN >> FP$$

$$\beta = 2$$

$$\boxed{F2\ score = (1+4)\ \frac{P * R}{P + R}}$$