Confusion Matrix

Foundation of binary classification metrics.

N = 100 Actual	Predicted Positive	 Negative	
Positive	30 (TP)	10 (FN)	40
Negative	5 (FP)	55 (TN)	60
	35	65	100

Terms:

TP: True Positive (Correct positive)
TN: True Negative (Correct negative)
FP: False Positive (Type I error)
FN: False Negative (Type II error)

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#1 Balanced Accuracy

Tests the model's ability to classify both positive and negative classes correctly.

Formula:

$$\text{Balanced Accuracy} = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right)$$

Use Case: In class-imbalance scenarios.

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#2 Precision

Measures how many of the predicted positive cases are actually positive.

Formula:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Use Case: Scenarios where false positives (misclassifying a genuine email as spam) need to be minimized.

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#3 Recall

Measures how many actual positive cases were correctly identified.

Formula:

$$\text{Recall} = \frac{TP}{TP + FN}$$

Use Case: Scenarios where missing a positive case (false negative) is critical.

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#4 F1-Score

Harmonic mean of Precision and Recall, balancing false positives and false negatives.

Formula:

$$F1 = 2 \times \frac{TP}{2TP + FP + FN}$$

Use Case: Considers both Precision and Recall.

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#5 Matthews Correlation Coefficient

A balanced measure considering all four confusion matrix elements, useful for imbalanced datasets.

Formula:

$$\mathrm{MCC} = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Use Case: Preferred over F1-score when both positive and negative classes are equally important, especially with imbalanced datasets.

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