

# Binary Classification Metrics Cheat Sheet

ROSCODE TECH

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This sheet covers useful metrics for binary classification, with consistent definitions, meanings, and worked examples. It also includes threshold-dependent curves for quick intuition.

## Contents

<b>1</b>	<b>Confusion Matrix and Notation</b>	<b>3</b>
<b>2</b>	<b>Core Metrics</b>	<b>3</b>
<b>3</b>	<b>Calibration Metrics</b>	<b>5</b>
<b>4</b>	<b>Threshold Curves</b>	<b>5</b>
<b>5</b>	<b>Quick Tips</b>	<b>6</b>

## 1 Confusion Matrix and Notation

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	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

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Total samples:  $N = TP + TN + FP + FN$ .

**Running example.** Unless stated otherwise, use:  $TP = 50$ ,  $FN = 10$ ,  $FP = 5$ ,  $TN = 35$ , so  $N = 100$ .

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## 2 Core Metrics

### Accuracy

$$Accuracy = \frac{TP + TN}{N}$$

**Meaning:** Fraction of all predictions that are correct.

**Example:**  $\frac{50+35}{100} = 0.85$ .

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### Sensitivity, Recall, True Positive Rate (TPR)

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

**Meaning:** Ability to find actual positives.

**Example:**  $\frac{50}{50+10} = 0.83$ .

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### Specificity, True Negative Rate (TNR)

$$Specificity = \frac{TN}{TN + FP}$$

**Meaning:** Ability to correctly reject actual negatives.

**Example:**  $\frac{35}{35+5} = 0.875$ .

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### Precision, Positive Predictive Value (PPV)

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

**Meaning:** Reliability of positive predictions.

**Example:**  $\frac{50}{50+5} = 0.91$ .

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## Negative Predictive Value (NPV)

$$NPV = \frac{TN}{TN + FN}$$

**Meaning:** Reliability of negative predictions.

**Example:**  $\frac{35}{35+10} = 0.78$ .

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## F1 Score

$$F1 = \frac{2(\text{Precision} \cdot \text{Recall})}{\text{Precision} + \text{Recall}}$$

**Meaning:** Harmonic mean of precision and recall. Encourages balance.

**Example:** With Precision = 0.91 and Recall = 0.83:  $F1 = \frac{2 \cdot 0.91 \cdot 0.83}{0.91 + 0.83} \approx 0.87$ .

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## Balanced Accuracy

$$\text{Balanced Accuracy} = \frac{1}{2}(\text{Recall} + \text{Specificity})$$

**Meaning:** Equal weight for positive and negative classes. Useful with imbalance.

**Example:**  $\frac{1}{2}(0.83 + 0.875) = 0.8525$ .

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## Error Rates (FPR, FNR)

$$FPR = \frac{FP}{FP + TN}, \quad FNR = \frac{FN}{TP + FN}$$

**Meaning:** FPR is the false alarm rate on negatives. FNR is the miss rate on positives.

**Example:**  $FPR = \frac{5}{40} = 0.125$ ,  $FNR = \frac{10}{60} \approx 0.167$ .

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## Matthews Correlation Coefficient (MCC)

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

**Meaning:** Correlation between prediction and truth. Robust under class imbalance.

**Example:**  $\frac{50 \cdot 35 - 5 \cdot 10}{\sqrt{55 \cdot 60 \cdot 40 \cdot 45}} \approx 0.74$ .

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## Cohen's Kappa

$$\kappa = \frac{p_o - p_e}{1 - p_e}, \quad p_o = \frac{TP + TN}{N}, \quad p_e = \frac{(TP + FN)(TP + FP) + (TN + FP)(TN + FN)}{N^2}$$

**Meaning:** Agreement beyond chance.

**Example:**  $p_o = 0.85$ ,  $p_e = \frac{3300 + 1800}{10000} = 0.51$ , so  $\kappa = \frac{0.85 - 0.51}{1 - 0.51} = 0.69$ .

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## Youden's $J$

$$J = \text{Sensitivity} + \text{Specificity} - 1$$

**Meaning:** Single summary of informedness.

**Example:**  $0.83 + 0.875 - 1 = 0.705$ .

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## Geometric Mean (G-Mean)

$$G\text{-Mean} = \sqrt{\text{Sensitivity} \cdot \text{Specificity}}$$

**Meaning:** Balance between catching positives and rejecting negatives.

**Example:**  $\sqrt{0.83 \cdot 0.875} \approx 0.852$ .

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## 3 Calibration Metrics

### Log Loss (Cross Entropy)

$$\text{LogLoss} = -\frac{1}{N} \sum_{i=1}^N \left[ y_i \log(p_i) + (1 - y_i) \log(1 - p_i) \right]$$

**Meaning:** How well predicted probabilities match outcomes. Lower is better.

**Example:** If a positive is predicted with  $p = 0.9$ , contribution is  $-\log(0.9) = 0.105$ . If it was actually negative, contribution would be  $-\log(1 - 0.9) = 2.303$ .

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### Brier Score

$$\text{Brier} = \frac{1}{N} \sum_{i=1}^N (p_i - y_i)^2$$

**Meaning:** Mean squared error of predicted probabilities. Lower is better.

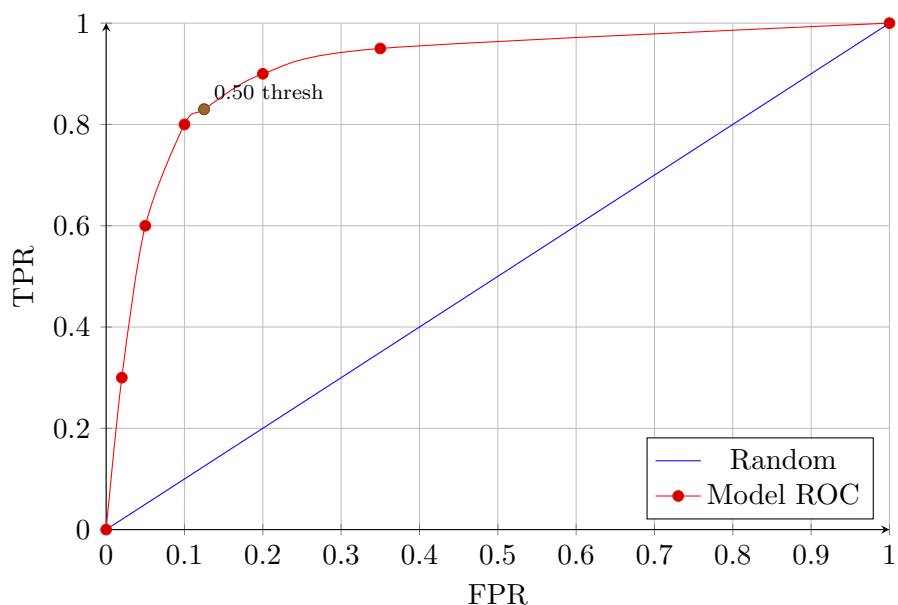
**Example:** For three cases with  $(p, y) = (0.8, 1), (0.4, 0), (0.3, 1)$ :  $\text{score} = \frac{(0.2)^2 + (0.4)^2 + (0.7)^2}{3} \approx 0.203$ .

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## 4 Threshold Curves

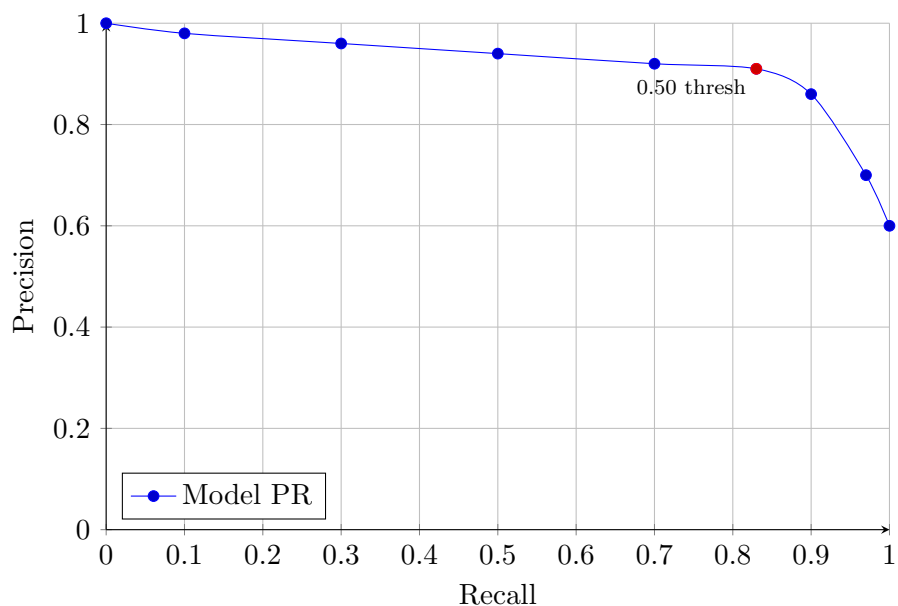
### ROC Curve and AUC

**Formula.** Plot  $TPR = \frac{TP}{TP+FN}$  against  $FPR = \frac{FP}{FP+TN}$  while sweeping the decision threshold from 1 to 0. **Meaning.** Trade-off between sensitivity and false alarms. **Example.** At threshold 0.50:  $TPR = 0.83$ ,  $FPR = 0.125$ .



## Precision–Recall Curve

**Formula.** Plot  $\text{Precision} = \frac{TP}{TP+FP}$  versus  $\text{Recall} = \frac{TP}{TP+FN}$  across thresholds. **Meaning.** Often more informative than ROC when positives are rare. **Example.** At threshold 0.50: Precision = 0.91, Recall = 0.83.



## 5 Quick Tips

- Use Balanced Accuracy, MCC, F1, and PR curves when classes are imbalanced.
- Move the threshold to trade precision for recall, or the reverse. Choose based on the application cost.
- F1 ignores true negatives. If true negatives matter, consider MCC or Balanced Accuracy.

- AUC is threshold independent, yet PR curves can be more revealing when positives are rare.
- Check calibration with Log Loss or Brier before using probabilities downstream.