Great question! Here's a clear and complete explanation of the most **important ML evaluation metrics and loss functions** you should know:

✅ Classification Metrics

1. Accuracy Score

- **Definition**: The ratio of correctly predicted observations to the total observations.
- **Formula**:

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

- **Use Case**: Works well when the data is balanced (e.g., spam detection where spam and non-spam are 50/50).
- **Limitation**: Misleading with imbalanced data.

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2. Precision Score

- **Definition**: The ratio of correctly predicted positive observations to the total predicted positives.
- **Formula**:

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

- **Use Case**: Useful when the cost of a false positive is high (e.g., email spam filter).
- **Tip**: High precision means low false positive rate.

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3. Recall (Sensitivity)

- **Definition**: The ratio of correctly predicted positive observations to all actual positives.
- **Formula**:

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

- **Use Case**: Critical when false negatives are costly (e.g., cancer detection).

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4. F1 Score

- **Definition**: Harmonic mean of precision and recall. Balances both in one number.

- **Formula**:

F1 Score=2·Precision·RecallPrecision+Recall\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}

- **Use Case**: Ideal when you need a balance between precision and recall.

✅ Regression Metrics

5. Mean Absolute Error (MAE)

- **Definition**: Average of absolute differences between predicted and actual values.
- **Formula**:

MAE=1n∑i=1n|yi−y^i|MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|

- **Interpretation**: Easier to understand because it's in the same unit as the target variable.

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6. Mean Squared Error (MSE)

- **Definition**: Average of squared differences between predicted and actual values.
- **Formula**:

MSE=1n∑i=1n(yi−y^i)2MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2

- **Use Case**: Penalizes larger errors more than MAE.
- **Limitation**: Sensitive to outliers.

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7. Root Mean Squared Error (RMSE)

- **Definition**: Square root of MSE.
- **Formula**:

RMSE=MSERMSE = \sqrt{MSE}

- **Use Case**: Same unit as target variable. Makes it easier to interpret error magnitude.

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8. R^2 Score (Coefficient of Determination)

- **Definition**: Proportion of variance in the dependent variable that is predictable.

- **Formula**:

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}$$

- **Range**: Between 0 and 1 (closer to 1 is better).
- **Use Case**: Measures model goodness of fit.

✅ Other Useful Metrics

9. Log Loss (Logarithmic Loss)

- **Definition**: Penalizes false classifications more harshly when predicted probabilities are wrong.
- **Use Case**: Probabilistic models (like Logistic Regression).

10. AUC-ROC Score

- **Definition**: Area under the Receiver Operating Characteristic curve.
- **Use Case**: Evaluates classifier performance across different thresholds.
- **Interpretation**: Higher AUC means better model separation between classes.

Summary Table

Metric	Type	Good For
Accuracy	Classification	Balanced datasets
Precision	Classification	Low false positives (e.g., spam)
Recall	Classification	Low false negatives (e.g., cancer)
F1 Score	Classification	Balance precision & recall
MAE	Regression	Simple average error
MSE	Regression	Penalize large errors
RMSE	Regression	Interpret magnitude of error
R^2 Score	Regression	Model fit
Log Loss	Classification	Probability accuracy

Metric	Type	Good For
AUC-ROC	Classification	Ranking model performance