Model Evaluation Metrics

Understanding Performance in Machine Learning

A Day in the Life of a Data Scientist

Confusion Matrix: The Foundation

All metrics start from the confusion matrix, which shows prediction outcomes:

- TP **True Positives:** Correctly predicted positive
- TN **True Negatives:** Correctly predicted negative
- FP **False Positives:** Incorrectly predicted positive (Type I error)
- FN **False Negatives:** Incorrectly predicted negative (Type II error)

Predicted

	Positive	Negative
Positive	TP	FN
Negative	FP	TN

Actual

Accuracy

What is it?

The proportion of correct predictions among all predictions made.

```
Accuracy = (TP + TN) / (TP + TN + FP + FN)
```

Example:

80 correct, 20 incorrect → Accuracy = 80%

When to use?

- Balanced datasets
- All errors equally important
- Quick performance assessment

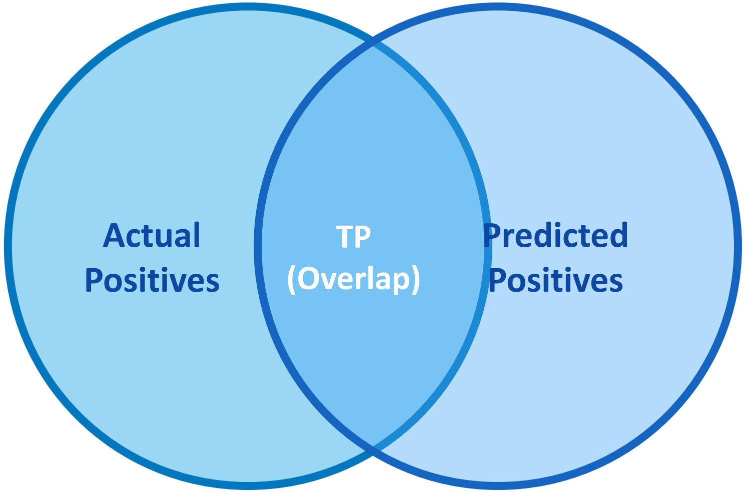
Limitations:

- Misleading with imbalanced classes
- Doesn't distinguish error types

Warning: 99% accuracy on 1% fraud data means always predicting "no fraud"!

Precision & Recall

Visual Understanding



Precision: Of what I predicted positive, how much was actually positive?

Precision

```
Precision = TP / (TP + FP)
```

Use when false positives are costly

- Spam filtering: Don't mark good emails as spam
- Medical tests: Avoid unnecessary treatments

Recall (Sensitivity)

```
Recall = TP / (TP + FN)
```

Use when false negatives are costly

- Disease screening: Don't miss sick patients
- Fraud detection: Catch all fraud cases

The Precision-Recall Tradeoff: Improving one often decreases the other!

F1-Score: The Harmonic Mean

What is it?

Harmonic mean of Precision and Recall, balancing both into a single score.

```
F1 = 2 × (Precision × Recall) / (Precision + Recall)
```

Punishes extreme imbalance and forces balance between both metrics.

When to use?

- Single balanced metric needed
- Imbalanced datasets
- Both error types matter

Example:

Model A: P=0.9, R=0.5 → F1=0.64

Model B: P=0.7, R=0.7 → F1=0.70

Model B wins!

The Imbalanced Dataset Problem

What is Label Imbalance?

When one class significantly outnumbers the other in training data.

Common Examples:

- **Fraud:** 99% legitimate, 1% fraud
- **Disease:** 95% healthy, 5% sick
- **Churn:** 90% retain, 10% leave

The Problem:

Models predict majority class and ignore the minority (often what we care about!).

Result: High accuracy, terrible recall on minority class!

SMOTE to the Rescue

Synthetic Minority Over-sampling Technique

How it works:

Creates realistic "fake" examples of the minority class by blending similar real examples together.

Example: If you have 2 fraud cases with similar patterns, SMOTE creates new synthetic fraud examples with features "in between" those two real cases.

```
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_train, y_train = smote.fit_resample(X, y)
```

From Probabilities to Predictions

Models Output Probabilities

ML models don't predict "yes" or "no" directly. They output a probability between 0.0 and 1.0.

Example predictions:

- Patient A: P(disease) = 0.95
- Patient B: P(disease) = 0.62
- Patient C: P(disease) = 0.31
- Patient D: P(disease) = 0.08

We set a threshold!

The Decision Threshold

Choose a cutoff value. If probability ≥ threshold, predict positive.

If threshold = 0.5:

- Patient A (0.95) → Predict: **Positive**
- Patient B (0.62) → Predict: **Positive**
- Patient C (0.31) → Predict: **Negative**
- Patient D (0.08) → Predict: **Negative**

Different thresholds = Different results!

Lower threshold → More positives predicted (higher recall, lower precision)
Higher threshold → Fewer positives predicted (lower recall, higher precision)

ROC-AUC: Evaluating All Thresholds

ROC Curve

Receiver Operating Characteristic: Shows model performance at every possible threshold.

```
TPR = Recall
FPR = FP / (FP + TN)
```

Each point on the curve represents a different threshold choice.

AUC Score

Area Under Curve: Performance across all thresholds.

1.0 = Perfect | 0.9+ = Excellent | 0.8+ = Good | 0.5 = Random

ROC Curve Visualization