Understanding ROC and AUC

A Practical Guide to Evaluating Binary Classification Models

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AGENDA

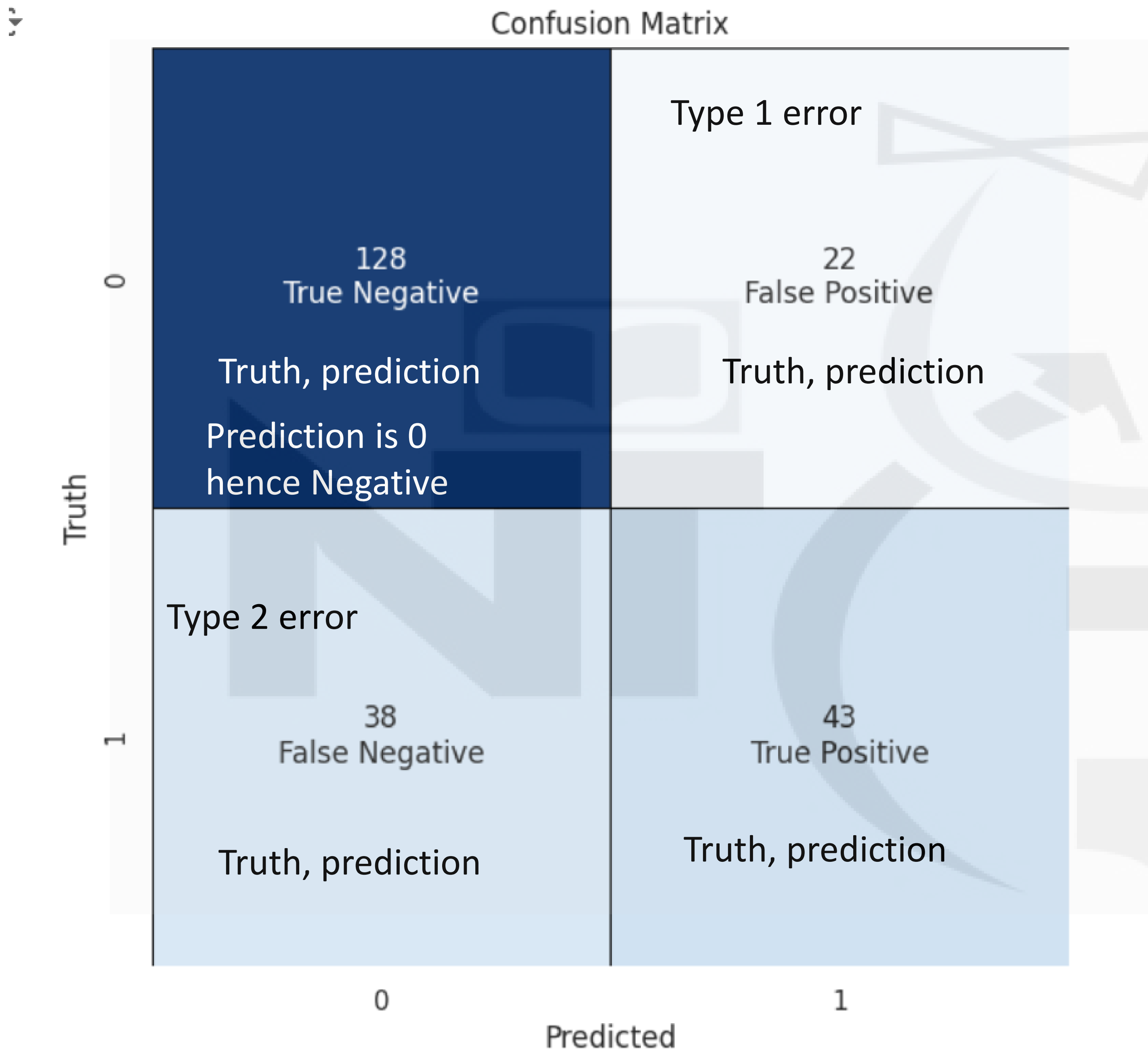
- What is ROC?
  - Receiver Operating Characteristic Curve.
- What is AUC?
  - Area Under the Curve.
- Importance:
  - **Used to evaluate and compare Binary classification models.**

What is ROC?

- ROC stands for **Receiver Operating Characteristic**.
- It is a graphical representation used to evaluate the performance of a **binary classification** model by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds.

Key Concepts

- **True Positive Rate (TPR):** Sensitivity, Recall.
- **False Positive Rate (FPR)**



Confusion Matrix
Type 1 error
128
True Negative
Truth, prediction
Prediction is 0
hence Negative
22
False Positive
Truth, prediction
Type 2 error
38
False Negative
Truth, prediction
43
True Positive
Truth, prediction
Truth
0
1
Predicted
0
1

True Positive Rate (TPR)

- **Also Known As:** Sensitivity, Recall
- The proportion of actual positive cases correctly identified by the model.
- It measures how effectively the model captures positive cases.

True Positive Rate (TPR)

$$\text{TPR} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Why It's Important:

- A high TPR indicates that the model is good at identifying positive cases.
- It's particularly crucial in scenarios where missing a positive case (False Negative) has a significant cost, such as detecting diseases.

False Positive Rate (FPR)

- The proportion of actual negative cases incorrectly identified as positive by the model.
- It measures how often the model falsely alarms.

$$\mathrm{FPR} = \frac{\text{False Positives (FP)}}{\text{False Positives (FP)} + \text{True Negatives (TN)}}$$

Comparison Between TPR and FPR

Metric	Focus	Ideal Value	Key Use Case
True Positive Rate	Captures positives correctly	**High (near 1)**	Diagnosing diseases, spam detection
False Positive Rate	Avoids false alarms	**Low (near 0)**	Fraud detection, security applications

Important Note

- **ROC/AUC is specifically applicable to classification models**, not regression models

- ROC (Receiver Operating Characteristic) curves and AUC (Area Under the Curve) are designed to evaluate a model's ability to **distinguish between classes** (e.g., positive and negative).

How ROC is Constructed

Steps:

- Vary the decision threshold.
- Calculate TPR and FPR for each threshold.
- Plot TPR vs. FPR.

- Explain in Notebook

AUC Explained

- AUC quantifies the area under the ROC curve.
- Ranges:
  - 1.0: Perfect model.
  - 0.5: Random guess.
- Importance:
  - Higher AUC means better model performance.

Practical Use Cases

- When to use ROC/AUC:
  - Imbalanced datasets.
  - Comparing multiple models.
- Real-world examples:
  - Medical diagnosis.
  - Fraud detection.

Limitations

- Refer notebook

Conclusion

- ROC helps visualize classification performance.
- AUC provides a single metric for comparison.
- Threshold tuning is crucial for optimizing model performance.

Code

```
from sklearn.metrics import roc_auc_score, roc_curve, auc
```

```
# Compute ROC curve and ROC area
fpr, tpr, _ = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, lw=2, label=f'{model_name} (AUC = {roc_auc:.2f})')
```

Lw = linewidth

- **Relationship to ROC Curve**
- The **ROC curve** plots **TPR** (y-axis) vs. **FPR** (x-axis) at various thresholds.
- An ideal model achieves:
  - **High TPR (close to 1)** for all thresholds.
  - **Low FPR (close to 0)**