ROC Curve, AUC, and Threshold Interpretation

Module 11.6 — Understanding probability thresholds and model performance evaluation in healthcare machine learning

Why Probability Matters in Clinical Decisions

1 Decision trees and most ML models don't output simple **Yes/No** predictions. Instead, they generate **probability scores** that reflect confidence levels.

2 These probabilities provide nuanced information about prediction certainty, enabling more informed clinical decision-making.

High Confidence

0.82 probability

Strong indication of disease presence

Low Confidence

0.30 probability

Lower likelihood of disease

Decision Point

0.50 default threshold

Where predictions split

What Is a Classification Threshold?

A threshold is the decision boundary that determines when to label a prediction as positive. It's the cutoff point where probability converts to action.

1

Threshold Rule

If probability ≥ 0.5 → Predict "Heart Disease"

2

Impact on Metrics

Changing threshold adjusts TP, FP, FN, precision, and recall

3

Clinical Tuning

Optimal threshold depends on medical context and risk tolerance

Why Threshold Selection Matters in Healthcare

High Threshold (0.7+)

- Fewer false alarms
- More missed patients
- Higher precision, lower recall

Low Threshold (0.3)

- Fewer missed patients
- More false alarms
- Lower precision, higher recall

Medical scenarios require **careful threshold tuning** based on clinical consequences, not blind acceptance of the 0.5 default.

The ROC Curve: Visualizing Model Performance

The **Receiver Operating Characteristic (ROC)** curve is a powerful visualization tool that evaluates classification performance across *all possible thresholds* simultaneously.

01

True Positive Rate

Proportion of actual positives correctly identified (Recall)

02

False Positive Rate

Proportion of actual negatives incorrectly classified as positive

03

Threshold Points

Each point on the curve represents one threshold value

04

Class Separation

ROC reveals how well the model distinguishes between classes

Understanding ROC Curve Axes

X-Axis: False Positive Rate

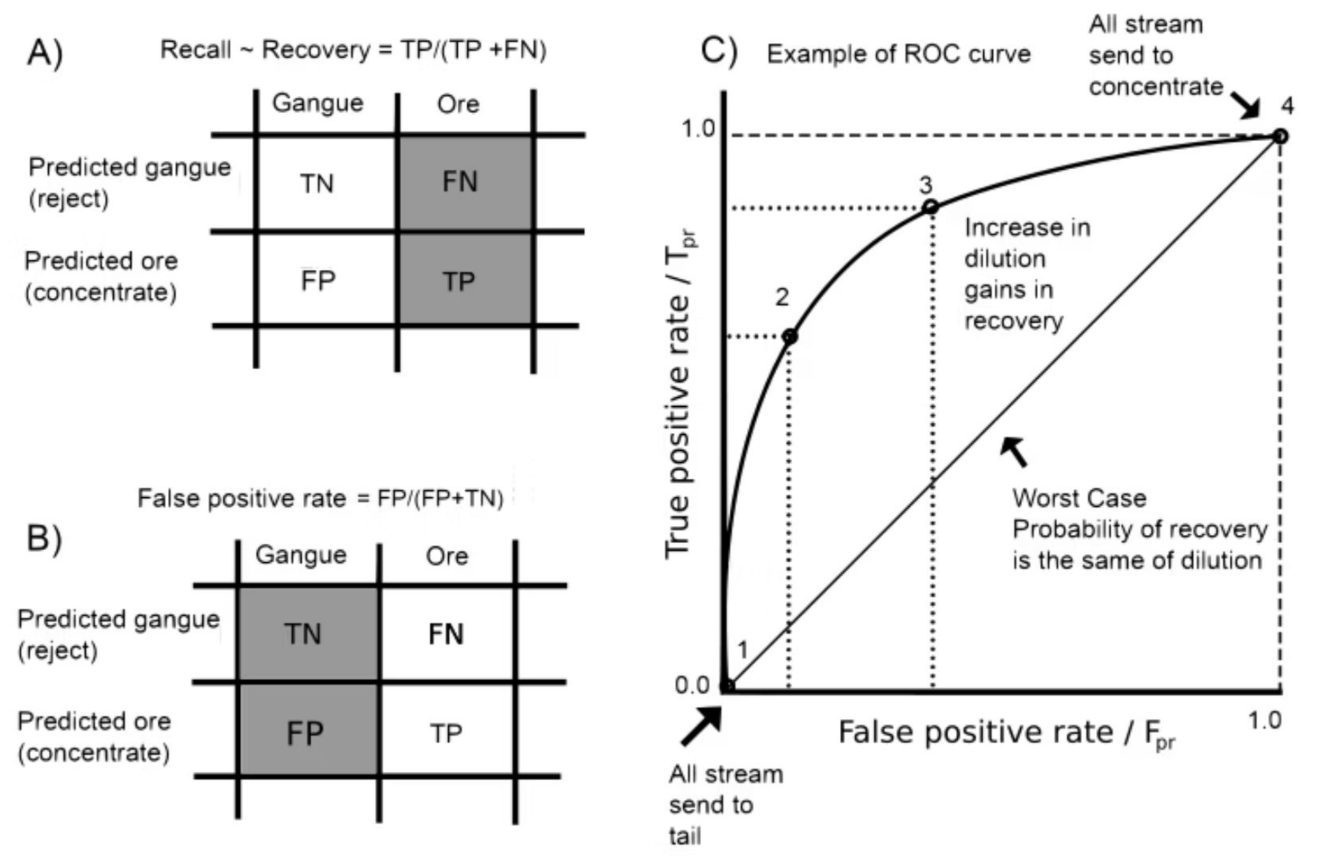
FPR = FP / (FP + TN)

Measures the proportion of healthy patients incorrectly flagged as having disease

Y-Axis: True Positive Rate

TPR = TP / (TP + FN)

Also called Recall — measures the proportion of sick patients correctly identified



The ideal model achieves **high TPR** (catching most disease cases) while maintaining **low FPR** (minimizing false alarms).

Interpreting ROC Curve Shape

Good Model

Smooth curve bending toward top-left corner

Random Guessing

Diagonal line from bottom-left to top-right

Broken Model

Curve falling below the diagonal — predictions are inverted

The closer the curve hugs the top-left corner, the better the model's discriminative ability across all threshold settings.

AUC: Summarizing ROC Performance

Area Under the Curve (AUC) condenses the entire ROC curve into a single interpretable metric, representing the probability that the model ranks a random positive case higher than a random negative case.

1.0	0.9	0.7	0.5
Perfect	Excellent	Acceptable	Random
Flawless separation	Strong performance	Useful for screening	No better than chance

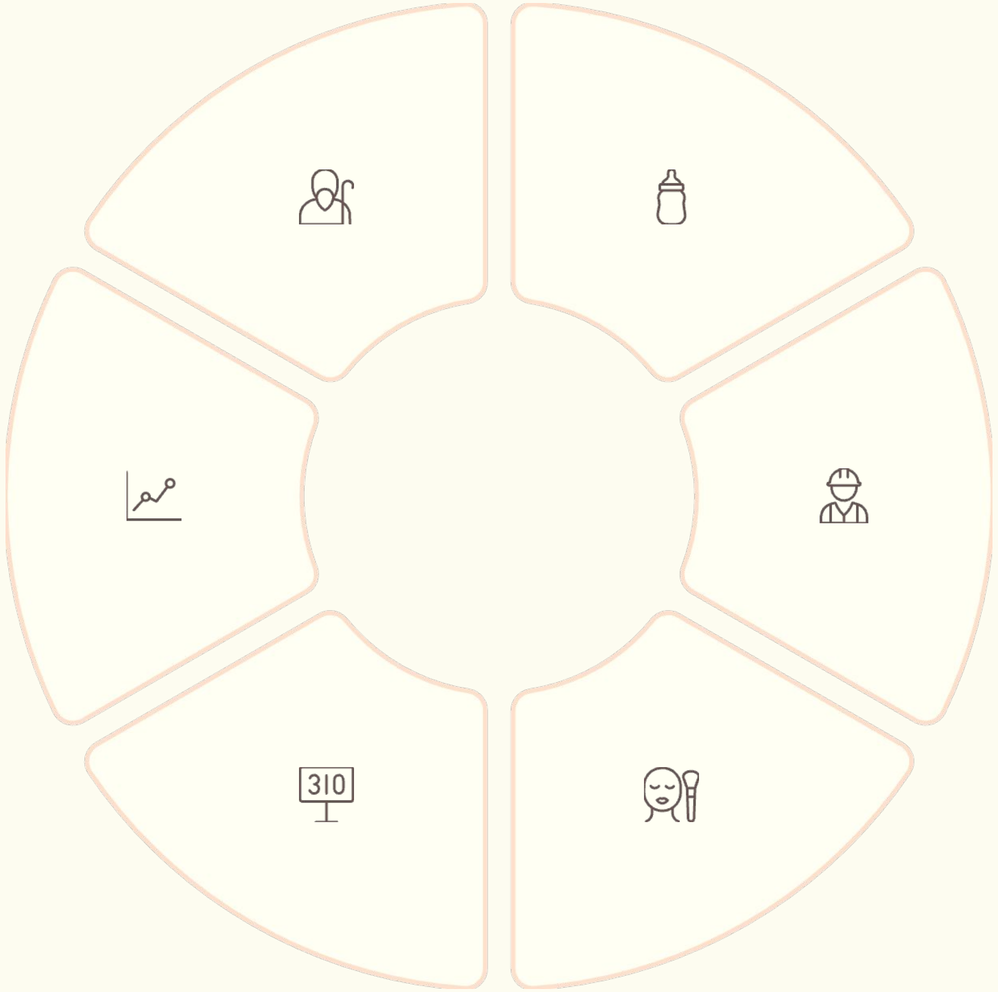
Module 11 Complete: Decision Trees Mastery

Tree Fundamentals

Structure, splits, and decision-making process

Core Concepts

Entropy, Gini impurity, information gain calculations



Model Building

Building and training your first tree classifier

Optimization

Overfitting prevention and pruning strategies

Evaluation

Confusion matrix, precision, recall, F1-score

Advanced Metrics

ROC curves, AUC, and threshold tuning

Decision Trees Excel At:

- Interpretability for clinical stakeholders
- Quick baseline model development
- Medical explainability requirements
- Handling mixed data types

Coming Next

Future modules will explore **ensemble methods** like Random Forests and Gradient Boosting that combine multiple decision trees for superior performance.