L04: Random Forests

Ensemble Learning for Robust Predictions

Methods and Algorithms – MSc Data Science

Learning Objectives

By the end of this lecture, you will be able to:

1. Explain how decision trees partition feature space
2. Implement Random Forests using bagging and feature randomization
3. Interpret feature importance and out-of-bag error
4. Apply ensemble methods to fraud detection problems

Finance Application: Fraud detection with interpretable feature importance

From single models to ensemble methods that combine many weak learners

The Business Problem

Fraud Detection Challenge

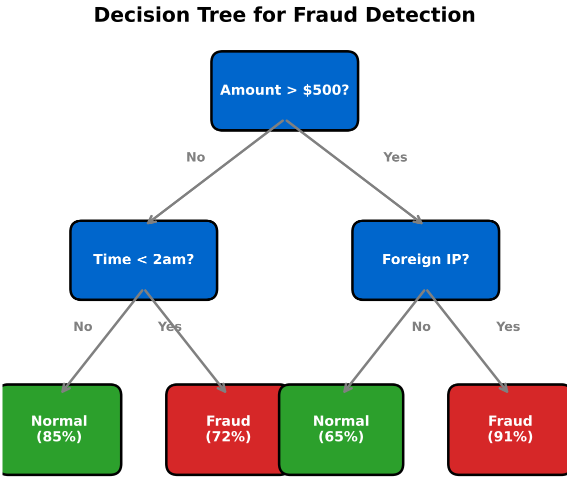
- Need high accuracy: fraudulent transactions cost millions
- Need interpretability: explain why transaction flagged
- Complex patterns: fraud evolves and adapts

Why Random Forests?

- Combines many trees for robust predictions
- Built-in feature importance ranking
- Handles non-linear relationships naturally

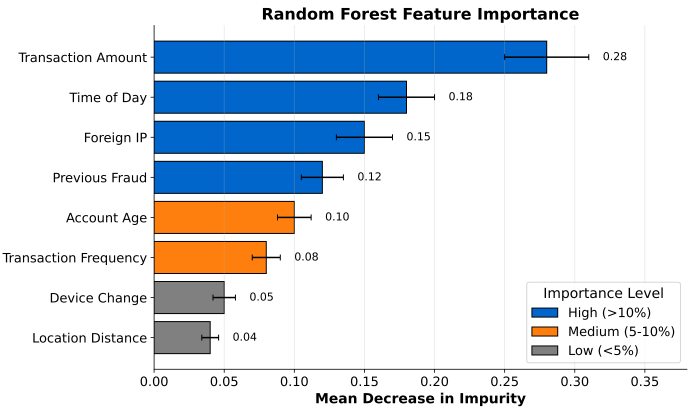
Ensemble methods: "wisdom of crowds" for machine learning

Decision Tree Structure



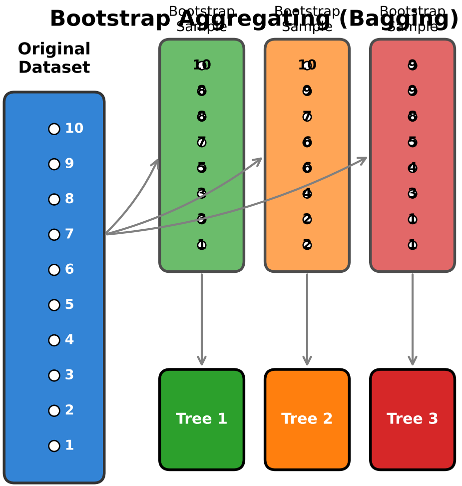
Trees split data using simple rules at each node until reaching a prediction

Feature Importance



Random Forests automatically rank which features matter most for prediction

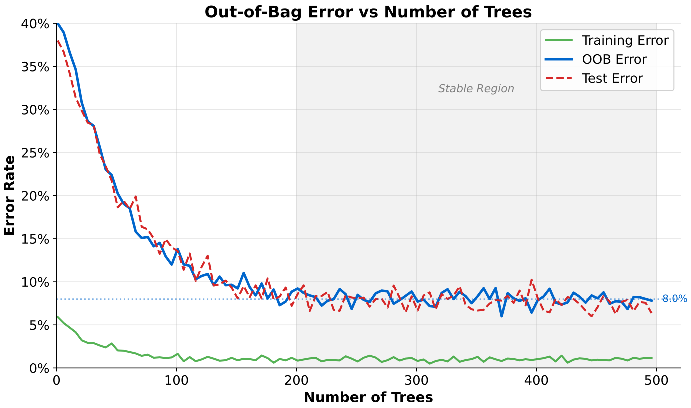
Bootstrap Aggregating (Bagging)



Each tree trained on ~63% unique samples (with replacement)

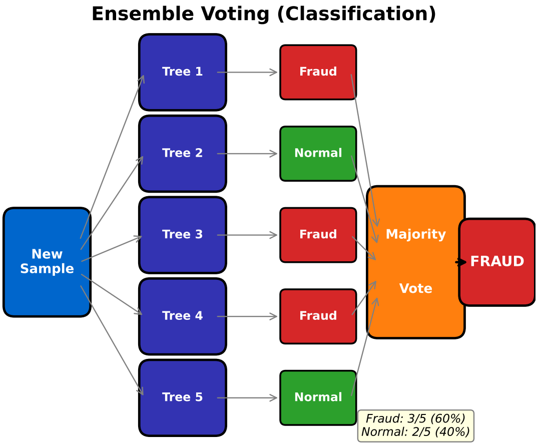
Each tree trains on a random sample, reducing overfitting

Out-of-Bag Error



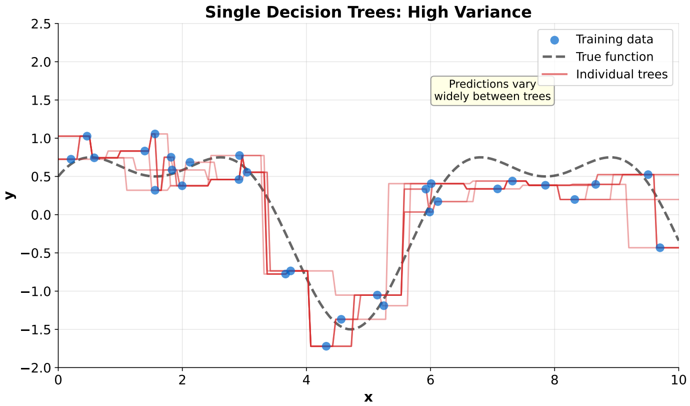
OOB error provides free cross-validation without held-out test set

Ensemble Voting



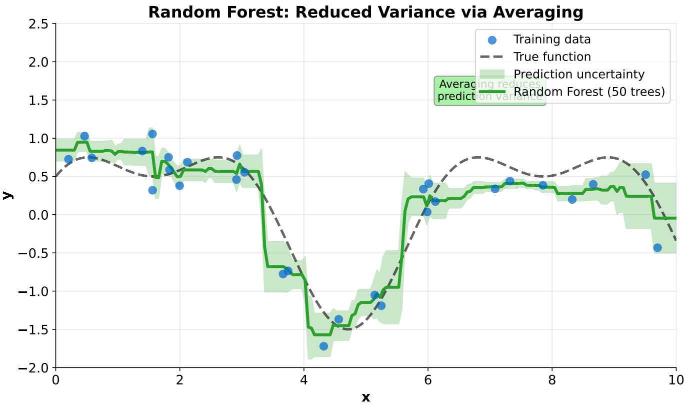
Final prediction combines votes from all trees (majority for classification)

Single Trees: High Variance



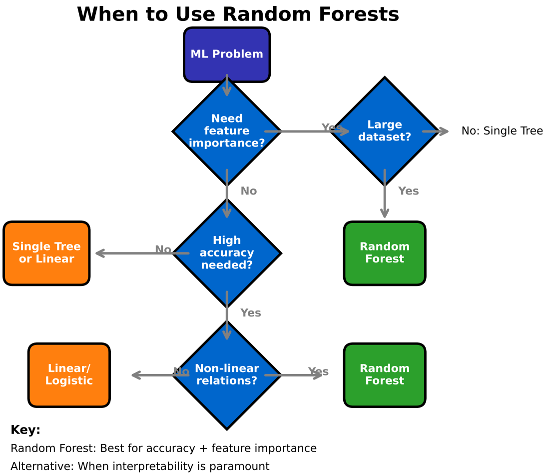
Each tree trained on different bootstrap sample produces different predictions

Random Forest: Reduced Variance



Averaging many high-variance trees produces low-variance ensemble

Decision Framework



Random Forests excel when accuracy and feature importance both matter