

L04: Random Forests

Ensemble Learning for Robust Predictions

Methods and Algorithms

Spring 2026

- 1 Problem
- 2 Method
- 3 Solution
- 4 Practice
- 5 Decision Framework
- 6 Summary

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

Fraud Detection Challenge

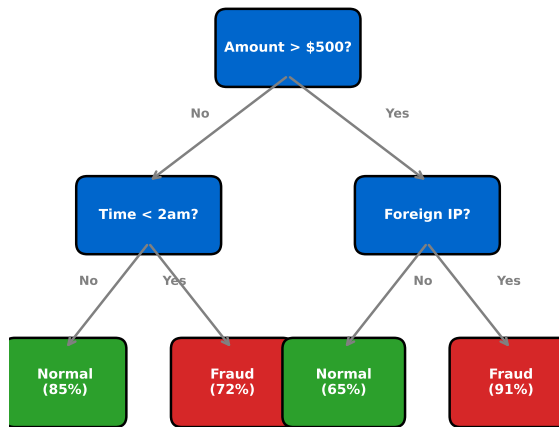
- Need high accuracy: fraudulent transactions cost millions
- Need interpretability: explain why transaction flagged
- Complex patterns: fraud evolves and adapts

Why Random Forests?

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

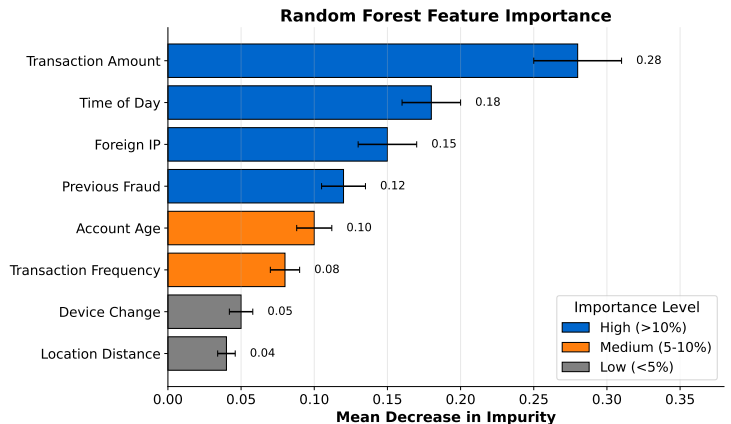
Ensemble methods: “wisdom of crowds” for machine learning

Decision Tree for Fraud Detection



https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/01_decision_tree

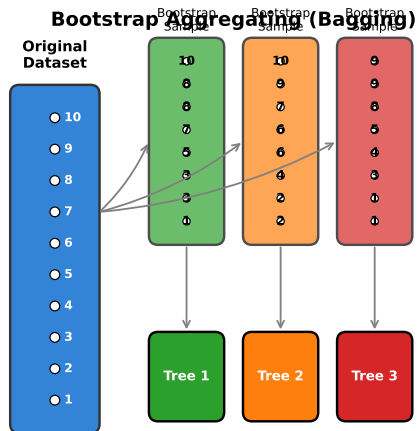
Trees split data using simple rules at each node until reaching a prediction



https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/02_feature_importance

Random Forests automatically rank which features matter most for prediction

Bootstrap Aggregating (Bagging)

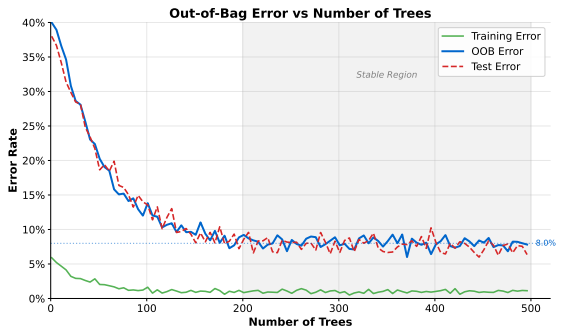


Each tree trained on ~63% unique samples (with replacement)

https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/03_bootstrap

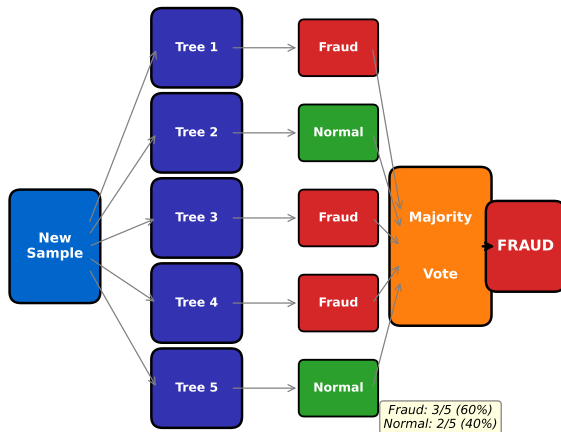
Each tree trains on a random sample, reducing overfitting

Out-of-Bag Error



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

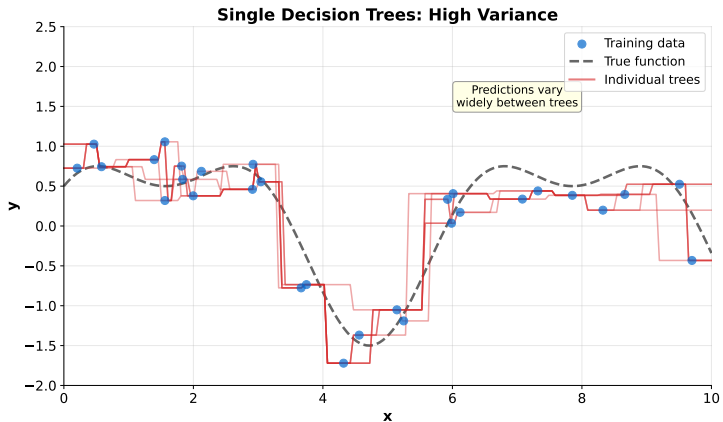
Ensemble Voting (Classification)



https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/05_ensemble_voting

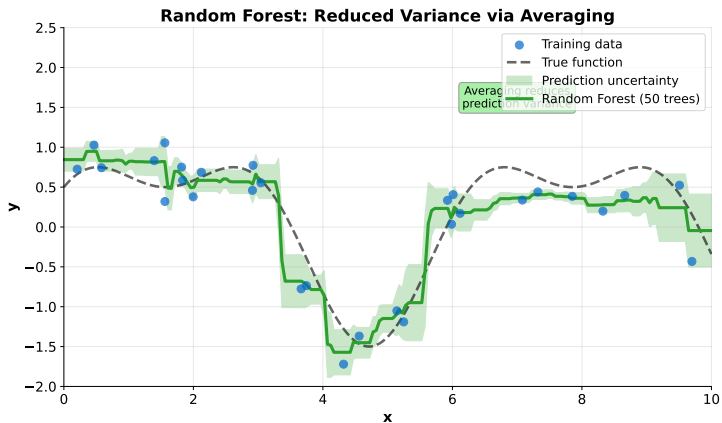
Final prediction combines votes from all trees (majority for classification)

Single Trees: High Variance



https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/06a_single_tree_variance

Each tree trained on different bootstrap sample produces different predictions



https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/06b_random_forest_variance

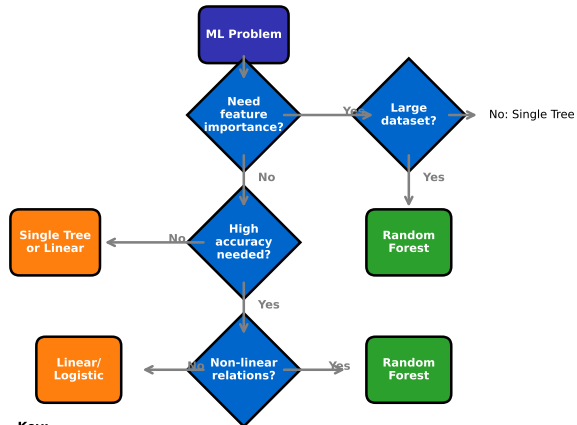
Averaging many high-variance trees produces low-variance ensemble

Open the Colab Notebook

- Exercise 1: Train a decision tree on credit data
- Exercise 2: Build a random forest and analyze feature importance
- Exercise 3: Tune hyperparameters with cross-validation

Link: <https://colab.research.google.com/> [TBD]

When to Use Random Forests



Key:

Random Forest: Best for accuracy + feature importance

Alternative: When interpretability is paramount

https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/07_decision_flowchart

Random Forests excel when accuracy and feature importance both matter

- Breiman, L. (2001). *Random Forests*. Machine Learning, 45(1), 5-32.
- James et al. (2021). *Introduction to Statistical Learning*. <https://www.statlearning.com/>
- Hastie et al. (2009). *Elements of Statistical Learning*. <https://hastie.su.domains/ElemStatLearn/>