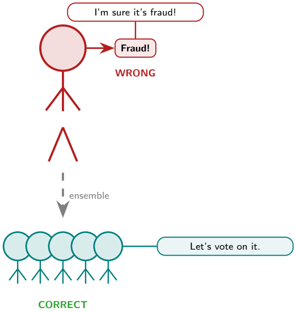
Why Would a Fraud Analyst Trust 500 Weak Detectors Over One Expert?

The Dilemma

- A single decision tree overfits to training noise
- High variance: different samples produce wildly different trees
- Two trees can disagree completely on the same transaction
- What if you let 500 imperfect trees vote?

Insight

RF combines many weak learners — variance drops without increasing bias.



Ensemble learning = combining imperfect models to produce reliable decisions

Polling the Room vs. Asking One Expert – Which Do You Trust More?

Think Before You Compute

Imagine asking one friend for a restaurant recommendation versus polling 20 friends. The single friend might have a strong bias (loves sushi, hates Italian). But 20 friends? Their biases cancel, and the consensus is more stable.

- How many friends would you ask?
- Did their individual biases cancel out?
- Was the consensus more stable than any single opinion?

Pause and reflect: when you last chose a restaurant by asking friends, you were bagging human opinions.

Reflection Prompt

Think of a time you made a better decision by gathering multiple opinions.

Bootstrap aggregating (bagging) formalizes this intuition: sample, train, average

What Makes a Random Forest Different from Bagging, Boosting, and a Single Tree?

Taxonomy of Ensemble Methods

Property	RF	Bagging	Boosting	Single Tree
Sampling	Bootstrap	Bootstrap	Sequential	All
Feature subset	$\sqrt{p}$	All	All	All
Tree correlation	Low	High	Sequential	N/A
Bias	Low	Low	Low	Low
Variance	Low	Medium	Low	High
Parallel	Yes	Yes	No	N/A

Random Forest
Vote of decorrelated trees

Bagging
Vote of correlated trees

Boosting
Sequential error correction

Single Tree
One fragile model

Insight

RF adds feature randomization **on top of** bagging to decorrelate trees.

Default split criterion: $G(p) = 1 - \sum_{k=1}^{K} p_k^2$ (Gini impurity)

Breiman (2001) showed feature randomization is what makes RF variance reduction superior to plain bagging

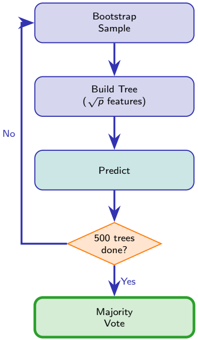
How Does a Single Transaction Navigate 500 Trees to a Fraud Verdict?

One Transaction, 500 Votes

- Bootstrap sample 63.2% of training data per tree
- At each split, consider only $\sqrt{p}$ random features
- Each tree votes: fraud or legit
- Majority vote = final prediction
- OOB samples validate without a held-out test set

Insight

Each tree sees different data AND different features – this double randomness is the source of RF's power.

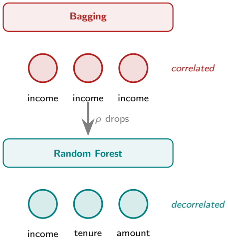


63.2% $= 1 - (1 - 1/n)^n \to 1 - 1/e$ **for large** n

How Does Feature Randomization Kill the Correlation Between Trees?

The Decorrelation Trick

- Bagging alone: if one feature dominates, all trees split on it — correlated — slow variance reduction
- RF fix: restrict each split to $\sqrt{p}$ random features — different trees use different features — ρ drops
- $\mathrm{Var}(\bar{f}) = \rho\sigma^2 + \frac{1-\rho}{B}\sigma^2$



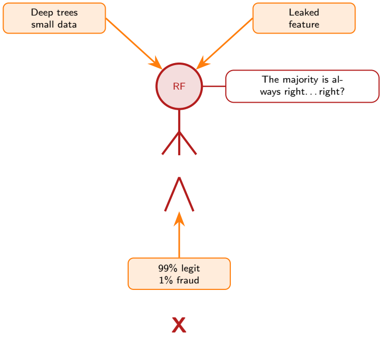
Insight

Reducing ρ is more powerful than increasing B.

Var(RF) $= \rho\sigma^2 + (1-\rho)\sigma^2/B$ **– the first term is the irreducible correlation floor**

Three Ways RF Can Still Fail

- **Overfitting to noise:** too many deep trees on small data
- **Feature leakage:** a feature that encodes the label
- **Class imbalance:** RF votes majority — rare class outvoted



Insight

Class imbalance is the #1 failure mode in fraud detection – always check class distribution.

Solutions: max_depth, min_samples_leaf, class_weight='balanced', SMOTE for resampling

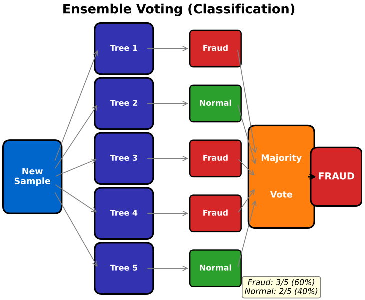
Why Do So Many Fraud Teams Reach for Random Forests First?

RF as the Industry Default

- Ensemble voting aggregates weak signals
- Feature importance reveals which attributes matter
- OOB error = free cross-validation
- Scales to millions with parallel training

Insight

RF popularity = simplest reasonable solution that works out of the box.



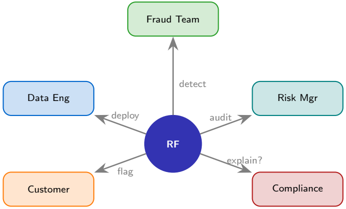
https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L04_Random_Forests/05_ensemble_voting

Kaggle surveys rank RF/gradient boosting as top methods for tabular data

Who Wins and Who Loses When Trees Replace Rules?

Stakeholder Analysis

- **Winners:** Fraud analysts (better detection), Risk managers (feature importance for audit), Data engineers (parallel, easy deploy)
- **Losers:** Compliance officers (less interpretable than logistic regression), Customers flagged by opaque ensemble



Insight

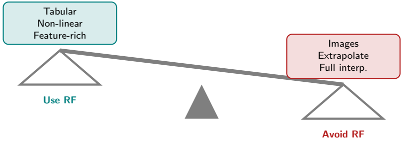
RF shifts fraud detection from human-crafted rules to data-driven patterns.

ECOA and GDPR require adverse action explanations – SHAP values bridge the gap

When Should You Reach for Random Forests – and When Should You Not?

The Decision Framework

1. **Is your data tabular?** If images/text → deep learning.
2. **Do you need probability calibration?** RF probabilities often poorly calibrated → Platt scaling.
3. **Must the model be fully interpretable?** If yes → logistic regression or single tree.



Insight

No Free Lunch: RF excels on tabular, non-linear, feature-rich data.

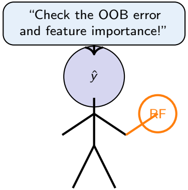
When in doubt: start with RF as baseline, then try XGBoost/LightGBM for marginal improvement

Can You Diagnose This Fraud Detection Model?

The Scenario

A payment processor runs RF with 1000 trees. Features: amount, time, merchant category, distance from home, device fingerprint. Flags 2% as fraud; actual fraud rate is 0.1%.

- Calculate the expected false positive rate
- Which feature likely ranks highest in importance?
- Model misses 40% of fraud – what would you change?
- Is the OOB error reliable here?



- ☐ OOB error
- ☐ Top 3 features
- ☐ Overfitting?
- ☐ Class balance

Deliverable

Fill in the table on the right.

Hint: with 0.1% fraud rate and 2% flag rate, most flags are false positives