L04: Random Forests

Full Lecture: Ensemble Learning, Variance Reduction, and Fraud Detection

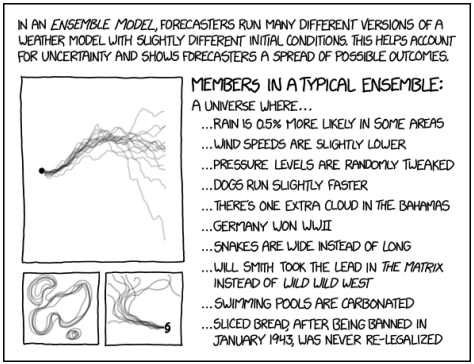
Methods and Algorithms

MSc Data Science

The Ensemble Approach

The cartoon captures the absurdity – and power – of combining models.

- One model is fragile; many models are robust
- Ensembles exploit the **wisdom of crowds**: independent errors cancel
- Random Forests, boosting, and stacking all follow this principle
- The key insight: **diversity** among models matters more than individual accuracy



XKCD #1885 by Randall Munroe (CC BY-NC 2.5)

Learning Objectives

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

1. **Derive** the variance reduction formula for ensemble averaging (Analyze)
2. **Evaluate** RF vs. boosting through the bias-variance lens (Evaluate)
3. **Analyze** feature importance: MDI, permutation, SHAP (Analyze)
4. **Apply** ensembles to fraud detection with class imbalance (Apply)
5. **Compare** RF, AdaBoost, gradient boosting, XGBoost (Evaluate)

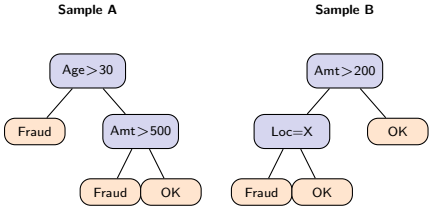
Bloom's Taxonomy Levels

- Analyze – break down, derive, compare components
- Evaluate – judge tradeoffs, assess suitability
- Apply – use methods on real data problems

L04 covers ensemble methods from bagging to boosting with finance applications.

Why Would a Single Tree Overfit Every Dataset It Touches?

- A fully grown tree has **low bias** (fits training data perfectly)
- But **high variance**: small data changes produce entirely different trees
- Bias-variance decomposition: $\text{MSE} = \text{Bias}^2 + \text{Variance} + \text{Noise}$
- Trees are **unstable learners** – ideal building blocks for ensembles



Different training samples $\Rightarrow$ completely different tree structures.

Insight

High variance is a *feature*, not a bug – it means trees are sensitive enough to be improved by averaging.

Unstable learners benefit most from ensemble methods (Breiman, 1996).

How Does a Tree Choose the Best Split? (Gini Impurity)

Gini Impurity measures how often a random sample would be misclassified:

$$G = 1 - \sum_{k=1}^{K} p_k^2$$

Binary case: $G = 2p(1-p)$

Worked example (fraud data):

- Node: 800 legit, 200 fraud $\Rightarrow p_{\text{fraud}} = 0.2$
- $G = 1 - (0.8^2 + 0.2^2) = 1 - 0.68 = 0.32$
- Best split minimizes weighted Gini of children

Split evaluation:

- Left child: 50 fraud / 100 total $\Rightarrow G_L = 0.50$
- Right child: 150 fraud / 900 total $\Rightarrow G_R = 0.28$
- Weighted: $\frac{100}{1000}(0.50) + \frac{900}{1000}(0.28) = 0.30$
- Gain: $0.32 - 0.30 = 0.02$

Properties:

- $G = 0$: pure node (one class only)
- $G = 0.5$: maximum impurity (binary)
- Computationally cheaper than entropy

Insight

Gini impurity is a *concave* function of class proportions – every split on a mixed node reduces impurity.

CART uses Gini by default; scikit-learn's DecisionTreeClassifier(criterion='gini').

What Does Entropy Add Beyond Gini?

Shannon Entropy:

$$H = -\sum_{k=1}^{K} p_k \log_2 p_k$$

Information Gain:

$$\text{IG} = H(\text{parent}) - \sum_j \frac{n_j}{n} H(\text{child}_j)$$

- Entropy is zero for pure nodes, maximal at uniform distribution
- IG selects the feature that reduces uncertainty the most
- C4.5 and ID3 algorithms use entropy; CART uses Gini
- **Regression trees:** use MSE reduction (variance reduction) as the splitting criterion instead of Gini/Entropy

Gini vs. Entropy Comparison:

Property	Gini	Entropy
Range (binary)	$[0, 0.5]$	$[0, 1]$
Computation	Faster	log needed
Sensitivity	Majority class	Rare classes
Algorithm	CART	C4.5, ID3

In practice, Gini and entropy produce **nearly identical** trees.

Insight

Entropy penalizes impure nodes slightly more than Gini – in fraud detection, this can surface rare-class splits earlier.

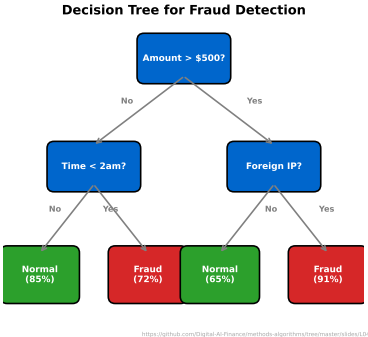
For binary classification, $H \approx 2G$ near $p = 0.5$; the choice rarely changes the final tree.

What Does a Trained Decision Tree Actually Look Like?

What you see: A tree trained on financial features, splitting recursively on the most informative thresholds.

Key pattern: Each internal node tests one feature; each leaf assigns a class or value. Deeper trees fit noise.

Takeaway: A single tree is interpretable but brittle – small data shifts change the entire structure.



Insight

Interpretability is the single tree's greatest strength – and its fragility is the motivation for ensembles.

Pruning (max_depth, min_samples_leaf) trades bias for variance reduction.

Why Does Averaging Multiple Models Reduce Variance?

Key derivation. For B models with variance σ^2 and pairwise correlation ρ:

$$\text{Var}\left(\frac{1}{B}\sum_{b=1}^{B} X_b\right) = \rho\sigma^2 + \frac{1-\rho}{B}\,\sigma^2$$

Two extreme cases:

- $\rho = 1$ (identical models): Var $= \sigma^2$ – no improvement
- $\rho = 0$ (independent models): Var $= \sigma^2/B$ – perfect scaling

The **goal of bagging**: reduce ρ by training on different bootstrap samples while keeping σ^2 large (deep trees).

Derivation sketch:

- $\text{Var}(\bar{X}) = \frac{1}{B^2}\sum_{i,j}\text{Cov}(X_i, X_j)$
- Diagonal terms: $B \cdot \sigma^2$
- Off-diagonal: $B(B-1)\rho\sigma^2$
- Combine: $\frac{1}{B^2}[B\sigma^2 + B(B-1)\rho\sigma^2]$
- Simplify to the variance formula above

Practical implication:
With $B = 500$ and $\rho = 0.05$:
Var $\approx 0.05\sigma^2 + \frac{0.95}{500}\sigma^2 \approx 0.052\sigma^2$

Insight

The first term $\rho\sigma^2$ cannot be reduced by adding more trees – only *decorrelation* can shrink it.

This is why Random Forests add feature randomization on top of bagging.

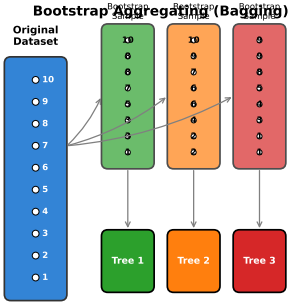
How Does Bootstrap Sampling Create Diversity?

What you see: Bootstrap resampling draws n samples with replacement from n observations.

Key pattern: Each bootstrap sample contains ∼63.2% unique observations; the remaining ∼36.8% are left out (OOB).

Takeaway: Bootstrap creates model diversity through data perturbation – each tree sees a different "view" of the training set.

- $P(\text{not selected}) = (1 - 1/n)^n \to 1/e \approx 0.368$
- Duplicates force trees to emphasize different patterns
- OOB samples become free validation data



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

Insight

Bootstrap is a "poor man's" way to approximate drawing from the true data-generating distribution.

Efron (1979) introduced bootstrap; Breiman (1996) applied it to tree ensembles.

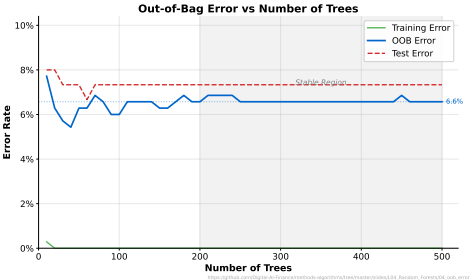
What Happens to the 36.8% of Samples Left Out?

What you see: OOB error converges as the number of trees grows, providing a built-in cross-validation estimate.

Key pattern: Each observation is OOB for $\sim$36.8% of trees. Aggregate their predictions to get an unbiased error estimate.

Takeaway: OOB error eliminates the need for a separate validation set – especially valuable when data is scarce.

- OOB error $\approx$ leave-one-out CV error
- No data "wasted" on validation
- Monitored automatically in scikit-learn with `oob_score=True`



Insight

OOB error is slightly pessimistic (each tree trained on $\sim$63% of data), making it a conservative estimate.

OOB error is one of Random Forests' most elegant properties – free, unbiased validation.

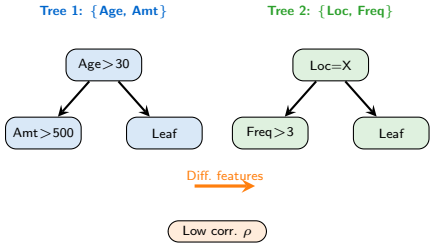
What Is the One Trick That Makes Random Forests Better Than Bagging?

Feature randomization. At each split, consider only a random subset of features:

- Classification: $m = \lfloor \sqrt{p} \rfloor$
- Regression: $m = \lfloor p/3 \rfloor$
- This forces trees to use **different features**, reducing correlation ρ

Why it works:

- Without randomization, every tree splits on the same dominant feature first
- Correlated trees $\Rightarrow$ correlated errors $\Rightarrow$ averaging helps less
- Feature subsampling **decorrelates** the trees



Insight

The "random" in Random Forests refers to feature subsampling at each split – not random data (that is bagging).

Breiman (2001): "Random Forests." Machine Learning, 45(1), 5–32.

How Does Feature Randomization Reduce Tree Correlation?

Recall the ensemble variance formula:

$$\text{Var}(\bar{f}) = \rho\,\sigma^2 + \frac{1-\rho}{B}\,\sigma^2$$

Effect of feature randomization on ρ:

- Bagging alone: $\rho \approx 0.5$–0.9 (trees still correlated)
- RF with $m = \sqrt{p}$: $\rho \approx 0.05$–0.2
- Smaller $m \Rightarrow$ lower ρ, but higher per-tree variance σ^2

The sweet spot:

- As $\rho \to 0$: Var $\to \sigma^2/B$ (ideal)
- Diminishing returns beyond $B \approx 500$ trees
- The $\rho\sigma^2$ floor is the irreducible ensemble variance

Method	ρ	B	**Var**
Single tree	1.0	1	σ^2
Bagging	0.6	500	$0.601\sigma^2$
RF ($\sqrt{p}$)	0.1	500	$0.102\sigma^2$
RF ($\sqrt{p}$)	0.1	1000	$0.101\sigma^2$

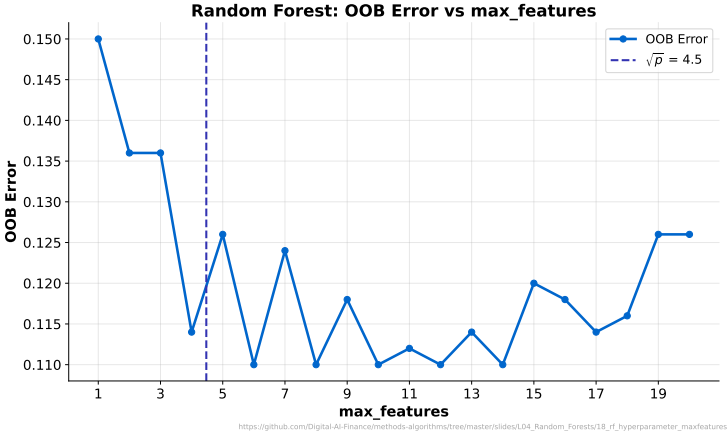
Note: going from 500 to 1000 trees barely helps once ρ dominates. The real gain comes from **reducing** ρ.

Insight

Decorrelation (reducing ρ) matters far more than adding trees (increasing B) – this is RF's core innovation.

In practice, tune max_features before n_estimators.

Feature Randomization: OOB Error Curve



OOB error as a function of max_features; dashed line marks $\sqrt{p}$, the typical default

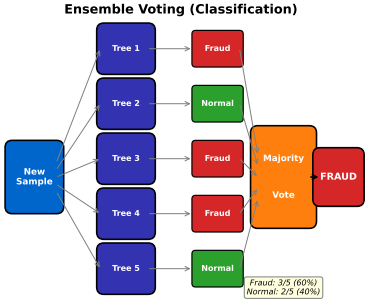
How Do 500 Trees Vote on a Single Prediction?

What you see: Individual tree predictions and the ensemble's aggregated vote for a single observation.

Key pattern: Individual trees disagree, but the **majority vote** converges to the correct class as B grows.

Takeaway:

- Classification: majority vote $\hat{y} = \text{mode}(\hat{y}_1, \ldots, \hat{y}_B)$
- Regression: average $\hat{y} = \frac{1}{B}\sum_{b=1}^{B} \hat{y}_b$
- Probability: fraction voting for each class
- Confidence grows with ensemble size and tree diversity



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

Insight

The Condorcet Jury Theorem guarantees: if each tree is better than random and errors are independent, the ensemble converges to perfect accuracy.

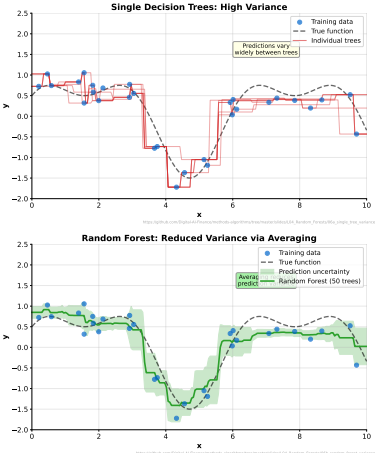
predict_proba() returns vote fractions – use these for ROC/AUC analysis.

Can You See the Variance Drop from One Tree to a Forest?

What you see: A single tree's jagged boundary (top) vs. the forest's smooth boundary (bottom).

Key pattern: The single tree overfits local noise; the forest averages it out.

Takeaway: Variance reduction made visible – averaging decorrelated trees smooths the prediction surface.



Insight

The forest does not learn a "better" tree – it averages *many different* trees to cancel out individual errors.

Top: single tree (high variance). Bottom: 500-tree forest (low variance, similar bias).

What Is the Random Forest Algorithm in Pseudocode?

Require: Training data $\{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$, number of trees B, feature subset size m

for $b = 1$ **to** B **do**
  Draw bootstrap sample $\mathcal{D}_b$ of size n
  Grow tree T_b on $\mathcal{D}_b$:
    At each node, select m features at random
    Find best split among these m features
    Split and recurse until stopping criterion
  Store T_b
end for

Ensure: Predict new $\mathbf{x}$:

Classification: $\hat{y} =$ majority vote of $\{T_b(\mathbf{x})\}_{b=1}^{B}$

Regression: $\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(\mathbf{x})$

Complexity:

- Training: $O(B \cdot n \log n \cdot m)$
- Prediction: $O(B \cdot \text{depth})$
- Embarrassingly parallel – each tree independent

Default hyperparameters:

- $B = 500$ (n_estimators)
- $m = \lfloor \sqrt{p} \rfloor$ (max_features)
- No max_depth (fully grown)
- min_samples_leaf $= 1$

Insight

The algorithm is trivially parallelizable – training time scales linearly with cores, making RF fast even on large datasets.

scikit-learn: RandomForestClassifier(n_jobs=-1) uses all available CPU cores.

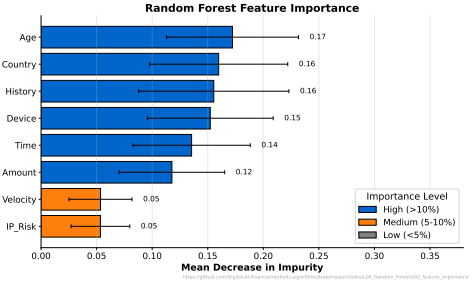
Which Features Matter Most? (Mean Decrease in Impurity)

What you see: Feature importance ranked by Mean Decrease in Impurity (MDI) across all trees.

Key pattern: MDI sums the Gini reduction from each feature across all splits in all trees:

$$\text{MDI}_j = \frac{1}{B} \sum_{b=1}^{B} \sum_{t \in T_b} \Delta G_{t,j}$$

Takeaway: MDI is fast and built-in (feature_importances_ in scikit-learn), but it has known biases.



Insight

MDI favors features used in many splits – not necessarily the features most predictive of the outcome.

Always cross-check MDI with permutation importance or SHAP for reliable conclusions.

Why Can MDI Be Misleading, and What Is Permutation Importance?

MDI bias:

- Favors **high-cardinality** features (many unique values ⇒ more split opportunities)
- Inflated for correlated features (importance is "shared")
- Computed on training data – can reflect overfitting

Permutation importance (model-agnostic):

1. Compute baseline score on held-out data
2. Shuffle feature j's values randomly
3. Re-score; importance = drop in performance
4. Repeat for all features

	MDI	Permutation
Data used	Train	Test/OOB
Bias	High-card.	None
Cost	Free	$O(p \cdot B)$
Model	RF only	Any model
Correlations	Inflated	Shared

scikit-learn: `permutation_importance(model, X_test, y_test)`

Insight

Permutation importance measures what the model *actually uses*; MDI measures what the model *could use*.

Strobl et al. (2007) first demonstrated MDI bias; always prefer permutation importance for final reporting.

How Do SHAP Values Explain Individual Predictions?

Shapley value from cooperative game theory:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!\,(p - |S| - 1)!}{p!} \left[f(S \cup \{j\}) - f(S) \right]$$

- ϕ_j = marginal contribution of feature j, averaged over all coalitions S
- Satisfies efficiency, symmetry, linearity, and null-player axioms
- $\sum_j \phi_j = f(x) - \mathbb{E}[f(X)]$ (predictions decompose exactly)

TreeSHAP (Lundberg et al., 2020):

- Exact Shapley values in $O(TLD^2)$ – polynomial, not exponential
- Exploits tree structure to enumerate coalitions efficiently
- Local (per-prediction) and global (averaged) explanations

Example: Transaction flagged as fraud
$\phi_{\text{amount}} = +0.32$
$\phi_{\text{location}} = +0.18$
$\phi_{\text{time}} = -0.05$
$\Rightarrow$ Amount and location drove the flag.

Insight

SHAP is the only feature attribution method with a *unique* solution satisfying all fairness axioms from game theory.

Lundberg & Lee (2017): "A Unified Approach to Interpreting Model Predictions." NeurIPS.

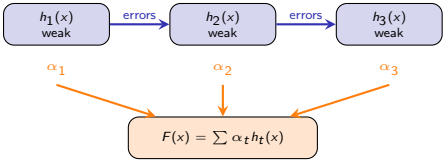
How Does Boosting Learn from Its Mistakes?

Core idea: Train weak learners **sequentially**, each focusing on the errors of the previous ensemble.

- **Bagging** (RF): parallel, reduces variance, full trees
- **Boosting**: sequential, reduces bias, shallow trees (stumps)
- Each new learner "corrects" the residual errors
- Final prediction: weighted sum of all weak learners

Three major algorithms:

- **AdaBoost** – reweights misclassified samples
- **Gradient Boosting** – fits residuals of a loss function
- **XGBoost** – regularized gradient boosting



Sequential: each learner corrects the combined errors of all predecessors.

Insight

Boosting reduces *bias* (makes weak learners strong); bagging reduces *variance* (stabilizes strong learners).

Schapire (1990) proved that weak learners can be "boosted" to arbitrary accuracy.

What Is AdaBoost's Weight Update Rule?

Learner weight (how much to trust learner t):

$$\alpha_t = \frac{1}{2} \ln \frac{1 - \epsilon_t}{\epsilon_t}$$

where ϵ_t = weighted error rate of h_t.

Sample weight update (Freund & Schapire notation):

$$w_i \leftarrow w_i \cdot \exp\bigl(-\alpha_t \, y_i \, h_t(x_i)\bigr)$$

where $y_i \in \{-1, +1\}$ and $h_t(x_i)$ is the weak learner prediction.

- When $y_i \neq h_t(x_i)$, the exponent is positive, increasing the weight
- Correctly classified: weight **decreased**; misclassified: weight **increased**
- Next learner focuses on hard examples
- Normalize weights to sum to 1

Properties of α_t:

- $\epsilon_t = 0$ (perfect): $\alpha_t \to \infty$
- $\epsilon_t = 0.5$ (random): $\alpha_t = 0$ (ignored)
- $\epsilon_t > 0.5$: $\alpha_t < 0$ (inverted)

Final prediction:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \, h_t(x)\right)$$

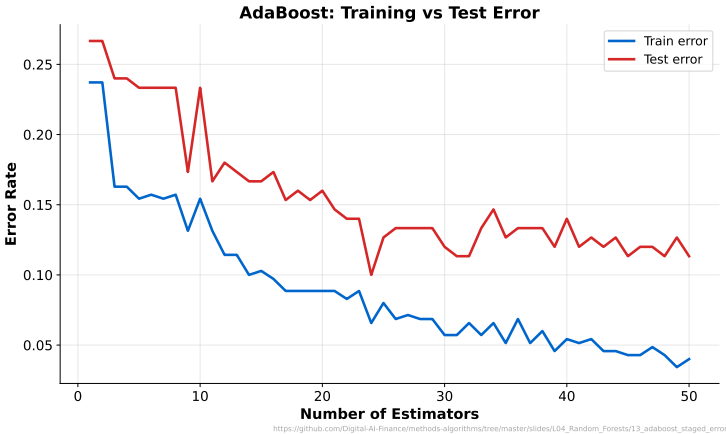
AdaBoost is equivalent to forward stagewise additive modeling with exponential loss.

Insight

AdaBoost's exponential loss makes it sensitive to outliers and label noise – a key limitation in noisy financial data.

Freund & Schapire (1997): "A Decision-Theoretic Generalization of On-Line Learning." JCSS.

AdaBoost: Training vs Test Error



AdaBoost reduces training error monotonically; test error plateaus as the ensemble converges

How Does Gradient Boosting Minimize an Arbitrary Loss?

Additive update:

$$f_m(x) = f_{m-1}(x) + \eta \cdot h_m(x)$$

where h_m fits the **negative gradient** of the loss:

$$r_{im} = -\left.\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right|_{f=f_{m-1}}$$

Squared loss: $r_{im} = y_i - f_{m-1}(x_i)$ (residuals)
Log loss: $r_{im} = y_i - \sigma(f_{m-1}(x_i))$
Learning rate $\eta \in (0, 1]$ shrinks each tree's contribution for regularization.

Algorithm:

1. Initialize $f_0(x) = \arg\min_\gamma \sum L(y_i, \gamma)$
2. For $m = 1, \ldots, M$:
   - Compute pseudo-residuals r_{im}
   - Fit tree h_m to $\{(x_i, r_{im})\}$
   - Update: $f_m = f_{m-1} + \eta \cdot h_m$
3. Output $f_M(x)$

Key hyperparameters:

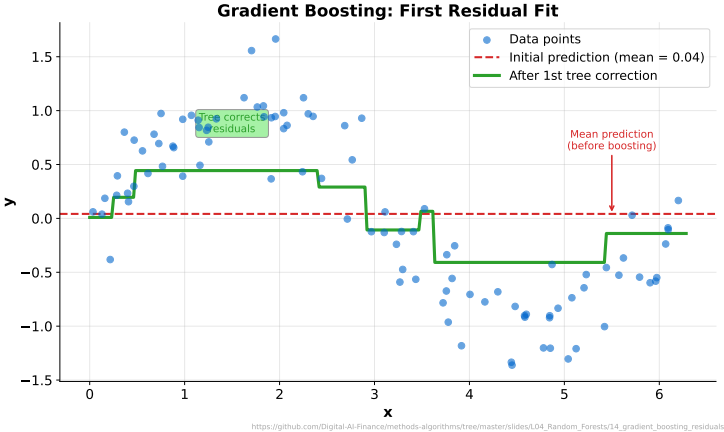
- M: number of boosting rounds
- η: learning rate (0.01–0.3)
- Tree depth: usually 3–8

Insight

Gradient boosting performs *gradient descent in function space* – each tree is a step toward the loss minimum.

Friedman (2001): "Greedy Function Approximation: A Gradient Boosting Machine." Annals of Statistics.

Gradient Boosting: First Residual Fit



The first tree fits the residuals (data minus mean), moving predictions toward the true function

What Makes XGBoost's Objective Function Special?

Regularized objective:

$$\mathcal{L} = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where the regularization term is:

$$\Omega(f) = \gamma T + \tfrac{1}{2}\lambda \|w\|^2$$

- T = number of leaves, w = leaf weights
- γ penalizes tree complexity (pruning)
- λ penalizes large leaf values (L2)

Second-order Taylor expansion:

$$\mathcal{L}^{(t)} \approx \sum_i \left[g_i f_t(x_i) + \tfrac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t)$$

where $g_i = \partial_{\hat{y}} L$, $h_i = \partial^2_{\hat{y}} L$.

Optimal leaf weight:

$$w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda}$$

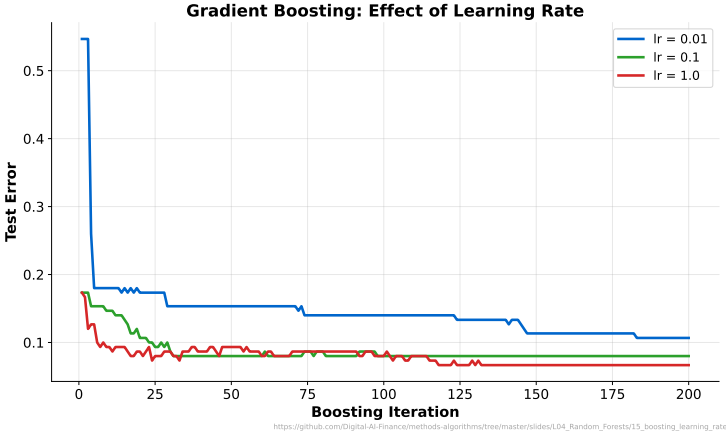
Using second-order info gives faster convergence than first-order gradient boosting.

Insight

XGBoost's regularization prevents overfitting *structurally* (fewer leaves) and *numerically* (smaller weights) – crucial for noisy financial data.

Chen & Guestrin (2016): "XGBoost: A Scalable Tree Boosting System." KDD.

Gradient Boosting: Effect of Learning Rate

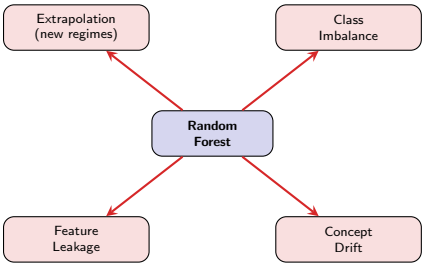


Smaller learning rates need more iterations but achieve lower test error—the regularization effect

When Does a Forest Fail Silently?

Four failure modes that produce **no error message** but wrong predictions:

- **Extrapolation:** RF cannot predict outside training range (piecewise constant). New market regimes break the model.
- **Class imbalance:** 99.9% legitimate $\Rightarrow$ "always predict legit" achieves 99.9% accuracy but catches zero fraud.
- **Feature leakage:** Future information in training features (e.g., post-transaction flags) inflates apparent accuracy.
- **Concept drift:** Fraud patterns evolve; a model trained in 2023 degrades by 2024.



All four produce high accuracy on historical data but fail in production.

Insight

Always evaluate on *temporally out-of-sample* data and monitor model performance continuously in production.

Silent failures are worse than crashes – they erode trust slowly and cause regulatory risk.

How Do You Choose the Right Hyperparameters?

Param	Default	Guideline
n_estimators	100	500+; more is rarely worse
max_depth	None	Limit to 10–20 for speed
min_samples_split	2	Increase to reduce overfit
max_features	$\sqrt{p}$	Try $\log_2 p$ for large p
class_weight	None	'balanced' for imbalance

- **Tuning order:** max_features $\rightarrow$ max_depth $\rightarrow$ n_estimators
- Use OOB score for quick evaluation
- Use cross-validation for final selection

Overfitting signals:

- Training accuracy $\gg$ test accuracy
- OOB error diverges from training error
- Feature importance dominated by noise features

Underfitting signals:

- Both training and test accuracy low
- Increase max_depth or n_estimators
- Check if max_features is too small

Rule of thumb: Start with defaults, increase n_estimators to 500, then tune max_features via grid search.

Insight

Random Forests are remarkably robust to hyperparameters – defaults often perform within 1–2% of the optimum.

Probst et al. (2019): "Hyperparameters and Tuning Strategies for Random Forest." WIREs Data Mining.

How Do Fraud Teams Use Feature Importance for Transaction Monitoring?

Worked case study:

Features: transaction amount, merchant category, time of day, customer age, distance from home, transaction frequency (last 24h), card-present flag.

Model: RF with 500 trees, class_weight='balanced', trained on 6 months of labeled data.

Top-5 by permutation importance:

1. Distance from home (ΔAUC = 0.08)
2. Transaction amount (ΔAUC = 0.06)
3. Frequency last 24h (ΔAUC = 0.04)
4. Time of day (ΔAUC = 0.03)
5. Card-present flag (ΔAUC = 0.02)

Actionable insights:

- **Distance:** Transactions far from home are the strongest fraud signal
- **Amount:** Large transactions need extra scrutiny, but amount alone is insufficient
- **Frequency:** Rapid-fire transactions suggest card testing
- **Time:** Late-night transactions correlate with fraud
- **Card-present:** CNP (card-not-present) transactions are riskier

These findings are presented to fraud analysts as SHAP waterfall plots for each flagged transaction.

Insight

Feature importance tells analysts *where to look*; SHAP tells them *why this specific transaction* was flagged.

Fraud teams combine model outputs with rule-based systems for final decisions.

What Happens When 99.9% of Transactions Are Legitimate?

The class imbalance problem:

- Fraud rate $\approx 0.1\% \Rightarrow$ 1 fraud per 1000 transactions
- Classifier predicting "always legit" gets 99.9% accuracy
- **Accuracy is meaningless** for imbalanced data

Solutions:

- `class_weight='balanced'`: upweight minority class inversely proportional to frequency
- **Stratified bootstrap:** ensure each tree's sample has proportional fraud cases
- **SMOTE:** synthetic minority oversampling (creates new fraud examples by interpolation)
- **Cost-sensitive learning:** $C_{FN} \gg C_{FP}$ (missing fraud costs more than false alarms)

Precision-recall tradeoff:

- **Precision:** Of flagged transactions, how many are actually fraud?
- **Recall:** Of all fraud, how many did we catch?
- Lowering threshold $\Rightarrow$ higher recall, lower precision
- Banks target **high recall** (catch fraud) at acceptable precision

Key metrics for imbalanced data:

- PR-AUC (precision-recall curve area)
- F1 or F_β score (weighted harmonic mean)
- Cost-weighted accuracy

Insight

In fraud detection, a false negative (missed fraud) costs 10–100x more than a false positive (unnecessary alert).

Use PR-AUC, not ROC-AUC, when the positive class is rare (Davis & Goadrich, 2006).

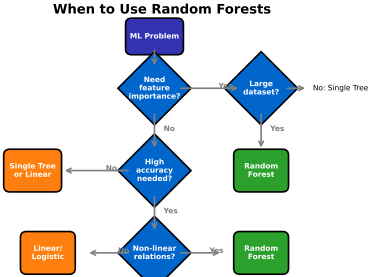
When Should You Choose RF Over Logistic Regression?

What you see: A decision flowchart guiding model selection based on data characteristics and requirements.

Key pattern:

- **Interpretability required?** ⇒ Logistic regression or single tree
- **Nonlinear relationships?** ⇒ RF or boosting
- **Many features, few samples?** ⇒ RF (implicit feature selection)
- **Maximum accuracy needed?** ⇒ XGBoost with tuning

Takeaway: No single model dominates; the right choice depends on the problem, data, and regulatory constraints.



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

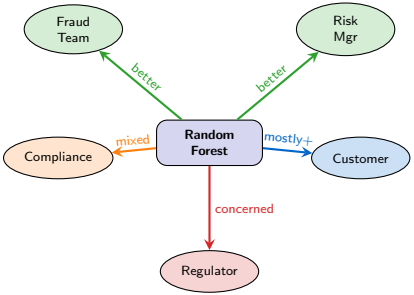
Insight

In regulated industries, the "best" model is often the one that is *explainable enough* to satisfy compliance – not the most accurate.

Many banks use RF internally but report logistic regression coefficients to regulators.

Who Wins and Who Loses When Ensembles Replace Scorecards?

- **Fraud Team:** Wins – better detection rates, fewer missed cases, faster adaptation
- **Risk Manager:** Wins – lower losses, better capital allocation, richer risk models
- **Compliance:** Mixed – improved outcomes but harder to audit 500-tree models
- **Customer:** Mostly wins – fewer false declines, but less transparent decisions
- **Regulator:** Concerned – demands explainability, adverse action reasons, fairness audits



Insight

The transition from scorecards to ensembles is a *governance* challenge as much as a technical one.

Successful adoption requires buy-in from all five stakeholders, not just data scientists.

Can Regulators Trust a Model Made of 500 Trees?

Regulatory landscape:

- **ECOA / Reg B (US):** Lenders must provide specific "adverse action reasons" for denial – hard with a forest
- **GDPR Article 22 (EU):** Right to "meaningful information about the logic involved" in automated decisions
- **EU AI Act:** High-risk AI systems (credit scoring) require transparency and human oversight

Bridging the gap with SHAP:

- SHAP provides per-decision explanations
- Top-k SHAP features $\Rightarrow$ adverse action reasons
- Global SHAP summary $\Rightarrow$ model documentation

Practical compliance workflow:

1. Train RF for optimal performance
2. Compute SHAP values for every prediction
3. Map top SHAP features to human-readable reason codes
4. Document model in a "model risk management" framework
5. Monitor for fairness across protected classes

SR 11-7 (Fed) requires banks to validate and document all models used in decision-making.

Insight

SHAP turns a "black box" into a "glass box" – the model is complex, but each decision is explainable.

The EU AI Act (2024) classifies credit scoring as "high-risk" – requiring explainability by law.

Key Takeaways

Mathematical Foundation

- Gini impurity and entropy guide tree splits; both yield similar results
- Variance of ensemble: $\rho\sigma^2 + \frac{(1-\rho)}{B}\sigma^2$ – decorrelation is key
- OOB error provides free, unbiased validation

Ensemble Methods Compared

- **Bagging/RF:** reduces variance via parallel, decorrelated trees
- **AdaBoost:** reduces bias via sequential reweighting
- **Gradient Boosting:** gradient descent in function space
- **XGBoost:** adds regularization and second-order optimization

Practical Application

- Feature importance: MDI $\rightarrow$ permutation $\rightarrow$ SHAP (increasing reliability)
- Fraud detection demands high recall, cost-sensitive learning, and PR-AUC evaluation
- Class imbalance: class_weight, SMOTE, stratified sampling
- SHAP bridges the gap between model complexity and regulatory explainability

Random Forests remain one of the strongest "out-of-the-box" classifiers two decades after Breiman (2001).

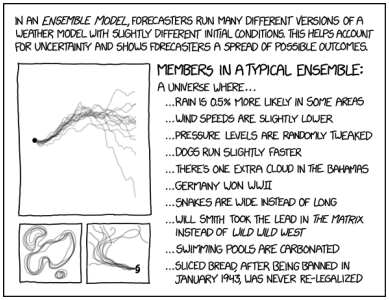
Until Next Time. . .

We opened with the absurdity of ensemble models (XKCD #1885).

Now you know **WHY** 500 trees beat one: **variance reduction through decorrelation**.

- One tree is interpretable but fragile
- Bagging stabilizes via bootstrap averaging
- Feature randomization decorrelates trees ($\rho \downarrow$)
- Boosting attacks bias where RF attacks variance
- SHAP makes the forest explainable for regulators

Next: L05 – PCA & t-SNE
From ensemble predictions to **dimensionality reduction** – how to visualize and compress high-dimensional financial data.



"The real power of ensemble models is not that each tree is good – it is that each tree is wrong in a different way."

XKCD #1885 by Randall Munroe (CC BY-NC 2.5) — L05 preview: PCA finds directions of maximum variance.