Digital Finance 3: Technology in Finance
Lesson 30: Credit Scoring and Risk Models

FHGR

December 7, 2025

Learning Objectives

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

- Compare ML credit scoring with traditional methods (FICO)
- Understand gradient boosting and tree-based models
- Recognize fairness and bias issues in credit decisioning
- Explain explainability requirements (GDPR, SHAP)
- Describe regulatory frameworks (EBA guidelines)
- Calculate PD and LGD metrics

FICO Score (Traditional):

- Range: 300-850
- 5 factors with fixed weights
- Linear scorecard model
- Only credit bureau data
- AUC: 0.65-0.75
- Transparent, regulated

Limitations:

- Linear assumptions
- One-size-fits-all
- Limited for thin-file borrowers

ML Approach:

- 100s-1000s of features
- Bureau + alternative data
- Non-linear (XGBoost, Random Forest)
- AUC: 0.75-0.85
- Higher accuracy

Business Impact:

- 10-30% default reduction
- Or 15-25% approval increase (same risk)

Trade-offs:

- Accuracy vs. interpretability
- Regulatory uncertainty
- Fairness concerns

Protected Attributes:
- Race, color, national origin
- Religion
- Sex, gender
- Age
- Marital status

The Problem:
- ML can learn biased patterns
- Proxy variables (zip code = race)
- Historical discrimination baked in

Fairness Metrics:
- Demographic parity
- Equal opportunity
- Equalized odds

Mitigation:
- Audit for disparate impact
- Re-weighting samples
- Constrained optimization
- Regular monitoring

Laws: ECOA, Fair Housing Act, GDPR Article 22

Key Takeaways:

- ML improves credit scoring accuracy by 10-20%
- Gradient boosting (XGBoost) dominates
- Fairness and bias are critical concerns
- Explainability required (SHAP values)
- Regulatory frameworks evolving (EBA guidelines)
- PD and LGD are core risk metrics

Next Lesson: Fraud Detection and AML