Digital Finance 3: Technology in Finance

Lesson 30: Credit Scoring and Risk Models

FHGR

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Summary of key concepts presented above.

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

Summary of key concepts presented above.

Traditional vs. ML Credit Scoring

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

Comparative analysis helps identify the right tool for specific requirements.

Fairness and Bias

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

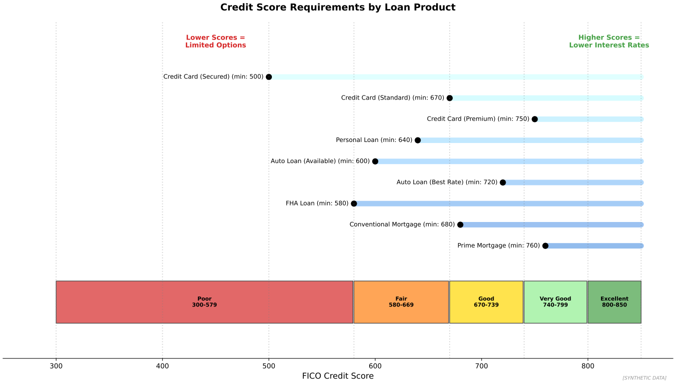
Mitigation:

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

Laws: ECOA, Fair Housing Act, GDPR Article 22

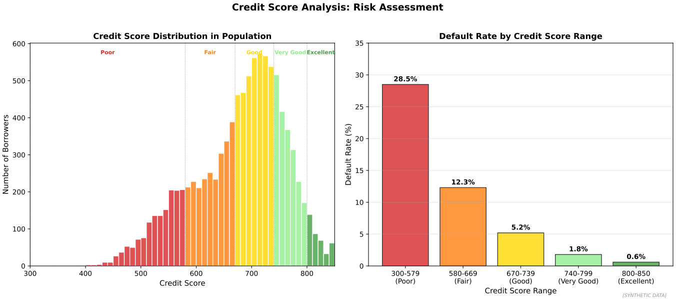
AI and ML are transforming financial services through automation and prediction.

FICO Score Ranges and Risk Categories



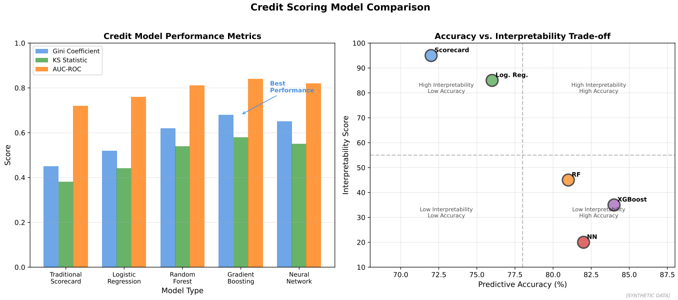
FICO scores range from 300 to 850, with higher scores indicating lower default risk.

Credit Score Distribution



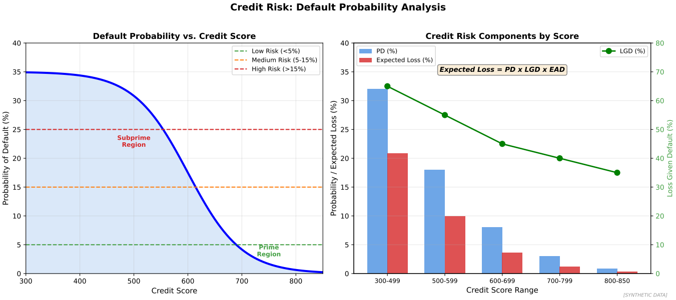
Credit scores typically follow a bell-shaped distribution, skewed toward higher scores.

Credit Model Comparison: Traditional vs. ML



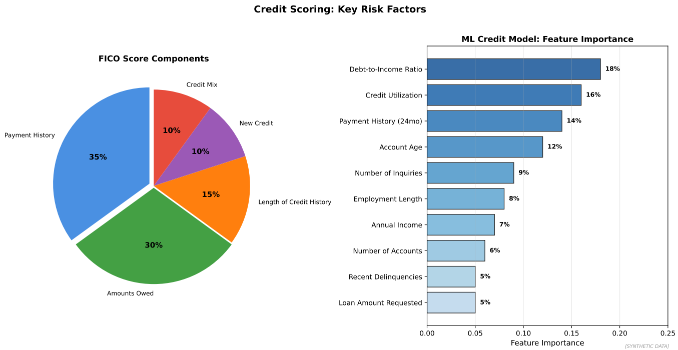
Machine learning models consistently outperform traditional scorecards in predictive accuracy.

Default Probability Curves



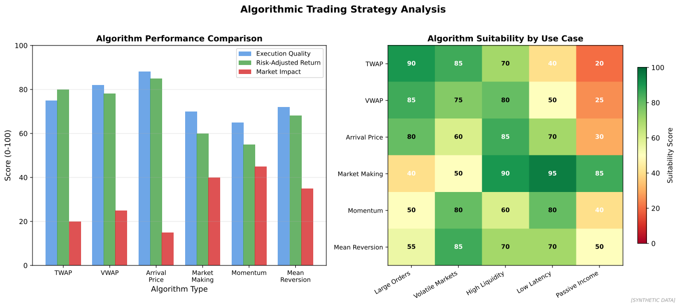
Default probability decreases non-linearly with credit score, demonstrating risk stratification.

Feature Importance in Credit Models



Payment history and credit utilization are typically the most predictive features in credit models.

Algorithm Performance Comparison



Gradient boosting methods like XGBoost consistently achieve the highest AUC scores in credit scoring.

Summary

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

Summary of key concepts presented above.