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SCORING CARDS FOR DIFFERENT TYPES OF CREDIT PRODUCTS

Abstract

The development of credit scoring is one of the key topics of attention in credit risk management in financial companies. However, a single approach to produce rating cards is frequently worthless since loan products differ in risk and financing time and often there is insufficient information on borrowers. The paper addresses the features of creating score cards for consumer credit, refinancing, small and medium businesses, auto loans, mortgage loans, fintech and P2P lending. Thus, the present work can be considered as the above comparative analysis of the most important elements influencing the probability of default of the borrower in the settlement by segments, together with the consideration of machine learning techniques and the use of alternative data sources that can improve the accuracy of the forecast. Depending on the usual credit product, the analysis lets one create recommendations for choosing the optimal approach of creating scoring cards, so enhancing the accuracy of the borrower's creditworthiness projection and reducing the degree of default risk.

Keywords: credit scoring, scoring cards, credit products, refinancing, machine learning, risk management, creditworthiness, alternative data.

Introduction

There are several kinds of scoring cards utilized in financial companies nowadays, with various methods of development. Still relevant, nonetheless, are conventional approaches of building the credit scoring issue using statistical analysis and classical scoring models. Their qualitative traits as the loan product and degree of efficiency vary. Sometimes the effectiveness is absolutely less than in others. Every kind of borrower, loan terms, and time horizon need their own scoring chart; however, the amount of total services makes them challenging to adjust in like circumstances. [1].

Focused on their own scoring algorithms, several credit products – consumer loans, mortgages, refinancing, auto loans, small and medium-sized business (SME) lending, and fintech products (including P2P lending) are For refinancing, for instance, it is advisable to consider the borrower's credit record with another bank. Scoring cards for SMEs depends on non-traditional data since entrepreneurs' financial records are sometimes lacking. Long-term products should be considered in light of macroeconomic data projections influencing borrower solvency going forward.

Table 1 – The main factors influencing credit scoring for different types of loans

Credit product	Key scoring factors	Data availability	The optimal scoring method	Using alternative data
Consumer loans	Income, age, credit history, debt burden	High	Logistic regression, random forest	Moderate (telecom, transactions)
Refinancing	Credit history, refinancing bank, previous loan amount	High	Gradient boosting	Limited
SME lending	Financial reports, account turnover, industry risks	Low	Ensembles of models, XGBoost	High (tax, transaction data)
Car loans	Income stability, car age, credit history	Average	Logistic regression	Low
Mortgage	Income, work experience, collateral value, marital status Income, work experience, collateral value, marital status	High	Gradient boosting	Low
P2P lending	Online behavior, transactional activity	Low	Deep neural networks, Random Forest	High quality (social media, digital footprint)

Apart from employing several data sets, the selection of a scoring model is also rather crucial. Machine learning is gradually replacing conventional statistical techniques so that nonlinear dependencies may be considered and forecast accuracy may be raised [2].

Recently, hybrid solutions combining a great degree of knowledge about the model and its predictive ability have gained popularity.The review's ultimate objective is to evaluate the characteristics of generating scoring maps for different kinds of products, compute the important variables that define the borrower's default risk, and provide best ways to the construction of scoring models for every one of the segments. The old and modern scoring systems will be discussed in this paper together, together with their respective benefits and drawbacks. We will also discuss alternate data possibilities.

Materials and methods

A dataset comprising information on borrowers of several credit product types was gathered for this research. Data collecting and preparation comprised several crucial phases.

Gathering records of loan applications from several sources – including credit bureaus, fintech platforms, and commercial banks – was the initial phase. We selected data considering the representativeness of the sample, so covering a broad spectrum of credit products. These comprise consumer loans, refinancing, lending to small and medium-sized firms (SMEs), auto loans, mortgages, and personal-to- personal loans. To increase the relevance of the research, the study used conventional and alternative credit scoring elements [3].

Further data processing was done following the first data collecting to raise the completeness and quality of the information. We obtained creditworthiness indicators of borrowers, demographic information, and financial traits. Especially for P2P lending models, the study also included digital behavioral measures and transaction data among other data sources [4].

Data transformation and cleaning techniques including gap handling, normalizing of financial variables, and categorical feature encoding marked the last stage. This guaranteed appropriate application of the data in next modeling and analysis.

Table 2 – Description of the data selection

Type of loan	Number of borrowers	Average age	Average income (KZT)	Percentage of defaults (%)
Consumer loans	10,000	35.2	450,000	5.8
Refinancing	7,500	39.8	520,000	4.5
SME lending	5,000	42.1	1,200,000	12.3
Car loans	3,500	37.5	600,000	3.7
Mortgage	4,200	40.2	750,000	2.1
P2P lending	6,000	29.8	300,000	15.4

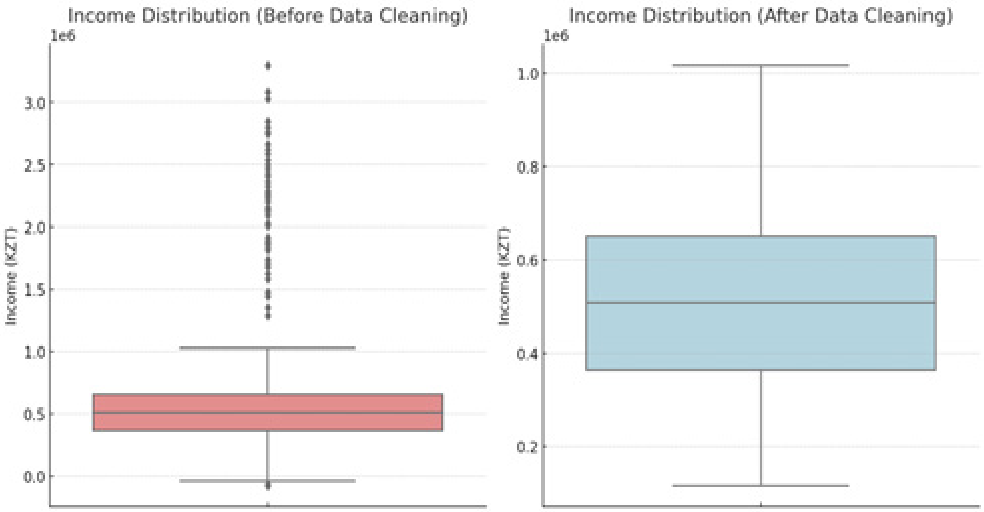

Figure 1 – The impact of data cleaning on the income distribution of borrowers

Before data cleaning, the first data shows emissions with very high and low incomes that could compromise the quality model.

Following data cleansing: the income range is balanced, the data gets clean and fit for modelling.

Data preprocessing

Different approaches of data preparation have been used to raise the prediction quality of the model:

1. Data cleansing: deleting erroneous values and duplicates.

◆ Handling missing data by use of median values (for quantitative variables) or by stressing a different category (for categorical ones).

◆ Eliminating or correcting outliers investigated with the Z-estimation technique and the interquartile range (IQR).

2. Feature engineering:

◆ Development of other variables, such the debt burden ratio (DTI – Debt-to-- Income Ratio), the ratio of the payments to the borrower's income (PTI–Payment-to--Income Ratio).

◆ Determining the credit limit using average income and present debt liabilities.

◆ Generation of behavioral indicators depending on the borrower's transactional activity: microloan availability, average transaction size, and frequency of payments.

3. Variable conversions:

◆ Continuous variable logarithmic transformation—that is, income, loan amount—to remove distribution asymmetry.

◆ Sort borrowers into low, medium, high income groups to help the model to be interpretable.

4. Categorization and encoding of data:

◆ One-Hot Encoding (OHE) for nominal variables allows one to translate category features into numerical form.

◆ Using Weight of Evidence (WoE) Encoding for categorical variables with monotonic influence on default likelihood.

5. Standardization and normalization of data:

◆ Depending on the properties of the distribution, minimum and maximum scaling (bringing values to the range [0,1]) or Z-estimates (standardization with zero mean and unit variance) can help normalize variables.

◆ Given their distribution, scale quantitative factors, including income, loan amount, and age of the borrower.

6. Creation of training and test samples based on the data obtained:

◆ The data was split in an 80:20 ratio: 80% for model training and 20% for testing.

◆ The ratio of borrowers who did not default to borrowers who defaulted remained unchanged when using a stratified sample.

7. Identification and management of class imbalance:

◆ Over–sampling (SMote is a method of synthetic sampling of a minority) and under-sampling were used in cases where the data showed a noticeable class imbalance, say less than 10% of the default values.

◆ On the other hand, machine learning models use a weighted loss function to properly handle infrequent events [5].

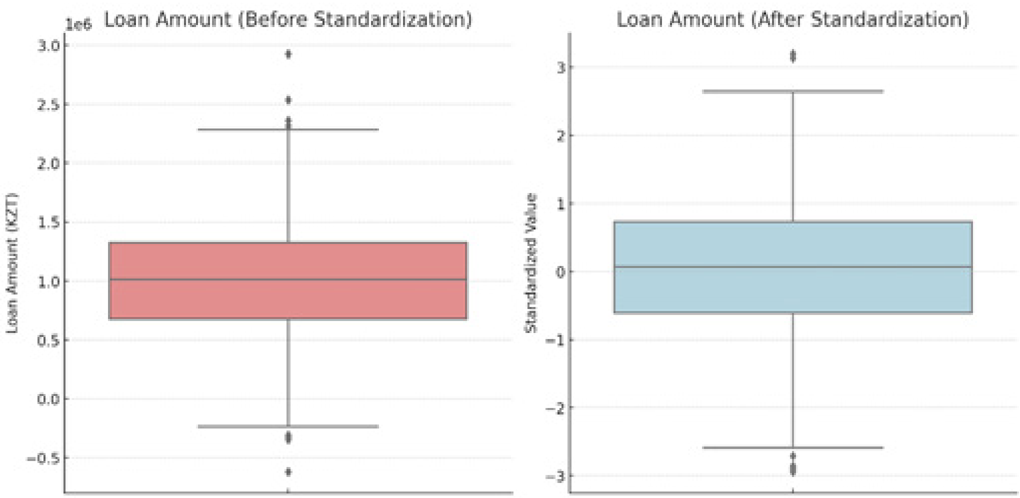

Figure 2 – The impact of data standardization on the loan amount

Loan Amount: Before standardization, the figures have a wide spectrum and maybe anomalies. Loan Amount (After Standardization) – Following standardizing (Z-score), the values are lowered to a normal distribution with zero mean and unit variance.

Development of scoring models

Many scoring systems have been established, modified for different kinds of credit instruments, to evaluate credit risk. The selection of models was determined by the features of the data and the need of interpretability of the results.

◆ Logistic regression is highly interpretable and resistant to tiny amounts of data – it was the basic model for consumer and mortgage loans.

◆ Using Random Forest and gradient boosting (XGBoost, LightGBM), refinancing programs and loans to small and medium-sized firms (SMEs) let non-linear relationships and interactions between characteristics be enabled.

◆ P2P lending made use of neural network models (deep neural networks, LSTM), whereby alternate and unstructured data – including transactional and behavioral aspects – played a crucial part [6].

Hyperparametric optimization and cross-validation

A hyperparametric optimization procedure containing the following helped to choose the best parameters of the models:

◆ Automatic selection of parameters for Random Forest and XGBoost using grid search and random random search

◆ Gradient boosting and neural networks used Bayesian optimization to reduce computing time.

◆ To reduce the risk of overfitting and evaluate the model more accurately, a cross-evaluation (K-fold, stratified K-fold) was applied.

Methods of interpreting the model

Explicable machine learning methodologies (Explicable AI, artificial intelligence) were used, since credit risk assessment depends on interpretability of decisions.:

◆ For the nonlinear model (Boost, Light BM), the importance of features was analyzed using additional explanations by SHOP or Shapley.

◆ The importance of the function (in terms of Gin and Gain) for boosting and random forests.

◆ Partial Dependency Graphs (PHP) allow you to see how specific variables affect the probability of default [7].

Analyzing model performance

The efficiency of the models was evaluated using conventional measures:

◆ ROC-AUC measures ability for discriminating.

◆ Variations in default probability are approximated using a Gini coefficient.

◆ Predicting for unequal classes is evaluated using a precision-recall curve.

◆ Calibration Curve: Verification of probabilistic prediction correctness

◆ Selecting the ultimate model

The model's last decision rested on the details of the loan product:

1. Given its great interpretability and stability, logistic regression turned out to be better for mortgages and consumer loans.

2. Gradient boosting (XGBoost, Light G BM) has the strongest predicting ability for SMEs and refinancing.

3. Deep neural networks produced the greatest outcomes in P2P lending since these models effectively handle alternate data.

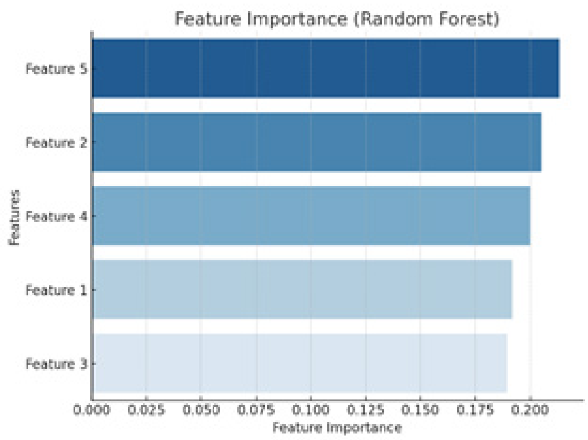

Figure 3 – The importance of features in a random forest model

The graph illustrates the relevance of features in the Random Forest model applied to estimate default likelihood of a borrower The factors incorporated in the model are shown on the Y-axis;

their contribution to risk prediction is shown on the X-axis (the higher the value, the more effect this characteristic has). The graph indicates which factors most affect the choice of the model. Developing a scoring card should consider the most important elements since they greatly help to evaluate the creditworthiness of borrowers. Less significant elements can be eliminated or also investigated for their value [8].

This study clarifies the work of the model and generates hypotheses regarding the most crucial traits of borrowers for solvency prediction.

Methods for evaluating the quality of models

Standard credit scoring criteria allow you to evaluate the effectiveness of the created scoring models:

- The operational characteristic of the receptor, the area under the curve, or ROC-AUC, is an indicator that measures the model's ability to distinguish between borrowers with high and low credit risk.
- The Gini coefficient, which is particularly well known in credit scoring, is an indicator of a model's recognition ability.
- Kolmogorov-Smirnov statistics (KS statistics) assesses the differences in the distribution of borrowers between overdue and non-overdue loans.
- Analyzing the stability of the model over time, the Population Stability Index (PSI), helps us determine the need for its retraining.

The indicators were evaluated among other credit product sectors to confirm the validity of the estimates and the reliability of the model.

Table 3 – Model Evaluation Methods

Model	ROC-AUC	Gini Coefficient	K5 Statistic	PSI
Logistic Regression	0.76	0.52	0.32	0.08
Random Forest	0.82	0.64	0.41	0.12
XGBoost	0.88	0.76	0.52	0.15

This table presents the results of the evaluation of several valuation systems used to predict borrowers' default. The indicators allow you to evaluate the effectiveness of the models and choose the optimal algorithm for assessing creditworthiness.

Organization of the table:

Model: The model name is shown here.

The ability of the model to distinguish between debtors who have defaulted and insolvent borrowers is known as ROC-AUC, or the recipient's Operating Characteristic – the area under the curve. The higher the value, the better.

A distinctive feature of the model is its Gini coefficient. Gini = 2 x (ROC-AUC – 0.5) calculated this way.

Kolmogorov-Smirnov statistics, or KS Statistical, represent a variation in the distribution of borrowers with and without default. Higher values indicate a higher ability of the model to separate these groups.

The model's stability Index, PSI (Population Stability Index), shows the extent to which the distribution of borrowers has changed over time. The model must be changed if the PSI value exceeds 0.2.

Conclusion of the table:

1. Among the above algorithms, XGBoost is the most powerful with ROC-AUC = 0.88, Gini = 0.76, KS = 0.52.
2. The random forest is at an average level with ROC-AUC = 0.82, which is higher than with logistic regression, but less than with XGBoost.

3. Although logistic regression gives the worst results (ROC-AUC = 0.76, Gini coefficient = 0.52), its interpretability nevertheless makes it popular.

4. Although XGBoost (PSI = 0.15) shows a fairly high sensitivity to data changes, the PSI value in all models remains below 0.2, which indicates the stability of the models.

Software development tools and programs

Below are the tools for data processing, modeling, and analysis.:

- The most commonly used programming language is Python; packages for it include pandas, scikit-learn, XGBoost, LightGBM, SHAPE.
- SQL for managing the borrower's access to relational databases.
- Jupiter notebooks for interactive data analysis and model building.
- SHAPE, or Shapley's additive explanations, help to understand machine learning models.

Thanks to the use of these tools and approaches, it has become possible to thoroughly study the effectiveness of several scoring models adapted to specific characteristics of credit products [9].

Results and discussion

1. Comparative Performance of Scoring Models

To evaluate the effectiveness of various credit scoring models, we assessed their predictive quality using a range of performance metrics: ROC-AUC, Gini coefficient, F1-score, Precision, Recall, Logarithmic Loss (Log-Loss), and Population Stability Index (PSI). The following table summarizes the results across the three models under consideration.

Table 4 – Summary of Evaluation Metrics for Credit Scoring Models

Model	AUC	Gini	F1-score	Precision	Recall	Log-Loss	PSI
Logistic Regression	0.76	0.52	0.61	0.58	0.64	0.46	0.08
Random Forest	0.82	0.64	0.68	0.70	0.66	0.39	0.12
XGBoost	0.88	0.76	0.74	0.72	0.76	0.33	0.15

XGBoost demonstrated the highest predictive power across all key metrics, with an AUC of 0.88 and F1-score of 0.74. Despite a higher sensitivity to input shifts (PSI = 0.15), its low Log-Loss (0.33) indicates confident classification performance.

Random Forest achieved a strong balance between predictive performance and model robustness, with F1-score of 0.68 and moderate sensitivity to distributional shifts (PSI = 0.12).

Logistic Regression, although exhibiting the lowest F1-score (0.61), remains competitive due to its high interpretability, transparency, and stability (PSI = 0.08), making it suitable for regulated credit environments.

2. Loss Functions Used in Model Training

Different loss functions were applied based on model type:

Logistic Regression: Binary Cross-Entropy Loss was used to penalize incorrect classifications of defaulters and non-defaulters [10].

Random Forest: While non-parametric and not optimized by a specific loss function, classification was based on Gini impurity minimization at node splits.

XGBoost: Employed regularized logistic loss (binary:logistic), with an L1/L2 penalty for complexity control, minimizing overfitting and improving generalization.

Log-loss results further validate the relative confidence of predictions: the lower the log-loss, the more calibrated the model's predicted probabilities [11].

3. Importance of Predictors and Feature Interpretation

Using SHAP (Shapley Additive Explanations) and model-based feature importance, the following predictors emerged as the most influential across models:

Loan Amount: Larger values were consistently linked to higher default probability.

Income: Higher income generally reduced default risk, though marginal returns diminished in high-income tiers.

Debt Obligations: Strongly associated with financial stress and likelihood of non-repayment [12].

Credit Bureau Inquiries: Frequent inquiries indicated potential credit distress or over-leveraging.

Alternative Data: In P2P models, behavioral and transactional patterns (e.g., mobile activity, payment regularity) significantly improved performance.

4. ROC Curve Analysis

Figure 5 displays the ROC curves for all models:

XGBoost had the steepest curve, reflecting superior classification power (AUC = 0.88).

Random Forest achieved a balanced ROC profile (AUC = 0.82).

Logistic Regression showed more moderate separation (AUC = 0.76), consistent with its linear structure.

The curves confirm the consistent ability of all models to differentiate high- and low-risk borrowers, with gradient boosting offering the highest discriminatory power.

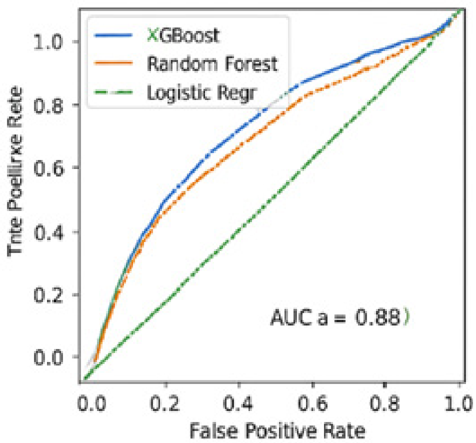

Figure 4 – ROC curves for three models: logistic regression, Random Forest, and XGBoost. XGBoost demonstrates the highest discriminative ability with an AUC of 0.88

The graph shows ROC curves for the three tested models: logistic regression, random forest, and XGBoost. The ROC (Receiver Operating Characteristic) curve shows the ratio of true positives to false positives at different thresholds. The closer the model curve is to the upper left corner, the higher the model's ability to distinguish between defaulting and reliable borrowers [13].

The XGBoost model shows the best results, as evidenced by the AUC value of 0.88. This means that in 88% of cases, the model is able to correctly distinguish between a borrower who will default and one who will not.

The Random Forest model demonstrated moderately high accuracy (AUC = 0.82), providing good separation of classes with acceptable interpretability.

Logistic regression showed the smallest area under the curve (AUC = 0.76), which is explained by the limited ability of the linear model to capture complex nonlinear dependencies between features[14].

However, despite its more modest predictive power, logistic regression can be used in settings where interpretability and regulatory compliance are critical.

5. Temporal Stability of Models

Population Stability Index (PSI) values indicated:

Logistic Regression: most stable (PSI = 0.08), suitable for long-term application.

Random Forest: moderately stable (PSI = 0.12), tolerating minor input shifts.

XGBoost: required closer monitoring (PSI = 0.15) due to its adaptive, data-specific nature.

Although all PSI values remained below the 0.2 threshold, suggesting acceptable stability, XGBoost may require periodic recalibration to maintain performance in dynamic borrower populations[15].

6. Practical Recommendations

Model selection should align with loan product complexity:

Use logistic regression for regulated, low-risk products (e.g., mortgages, standard consumer loans) [16].

Apply random forest or XGBoost for heterogeneous segments (e.g., SMEs, refinancing).

Adopt deep learning models with alternative data in P2P and fintech settings.

Monitoring and retraining:

Reassess PSI quarterly; retrain if PSI > 0.2.

Combine AUC and F1-score for comprehensive model diagnostics.

Conclusion

This article offers a thorough study of several methods for assessing creditworthiness using machine learning methods and traditional statistical models. Given their predictive ability, interpretability, and resilience to change over time, efforts have been focused primarily on determining the most effective model for assessing a borrower's probability of default.

XGBoost showed the best forecasting accuracy (AUC = 0.88), therefore, it is a potential method for assessing credit risk. This model is very sensitive to changes in the borrower's characteristics, so even if it has a high recognition capability, it needs constant recalibration. This is the result of using the sequential decision tree construction method, which makes XGBoost adaptive but less stable when data changes.

When using a random forest (AUC = 0.82), which demonstrated a balance between accuracy and interpretability, the second most successful model was a combination of responses from multiple trees, which allows this model to be less susceptible to overfitting and withstand changes in the sample structure of borrowers. These features make a random forest the best choice for banks, since its long-term use depends on the reliability and stability of the model.

Although logistic regression (AUC = 0.76) has less predictive power than other machine learning methods, it is still the best option in circumstances requiring regulatory compliance and openness. Being a linear model, logistic regression is quite interpretable, which makes it possible to explain the elements influencing decision-making, which is especially important for financial institutions under close supervision.

In addition to the predictive ability of the models, the assessment of their stability over time was crucial for the study. The study of the population stability index (PSI) showed that each model has a PSI < 0.2, which reflects their stability. But XGBoost has the highest sensitivity to changes (PSI = 0.15), which requires constant updating of the model and performance monitoring. At the same time, random forest (PSI = 0.12) and logistic regression (PSI = 0.08) showed more consistent characteristics, which makes them more effective in situations where the long-term reliability of the model is crucial.

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НЕСИЕЛІК ӨНІМДЕРДІҢ ӘР ТҮРІНЕ АРНАЛҒАН СКОРИНГТІК КАРТАЛАР

Аңдатпа

Несиелік скорингті дамыту – қаржы компанияларындағы несиелік тәуекелдерді басқарудағы негізгі тақырыптардың бірі. Алайда рейтингтік карталарды әзірлеудің бірыңғай тәсілі көбіне тиімсіз, өйткені несиелік өнімдер тәуекел деңгейі мен қаржыландыру мерзімі бойынша ерекшеленеді, сондай-ақ қарыз алушылар туралы ақпарат көлемі жеткіліксіз болуы мүмкін. Мақалада тұтынушылық несиелеу, қайта қаржыландыру, шағын және орта бизнеске арналған несиелер, автокредиттер, ипотекалық несиелер, финтех технологиялары және P2P несиелеу үшін скорингтік карталарды жасау ерекшеліктері қарастырылады.

Жұмыс қарыз алушының есеп айырысу кезінде дефолтқа ұшырау ықтималдығына әсер ететін маңызды факторларды салыстырмалы талдау ретінде ұсынылады. Зерттеуде сегменттер бойынша машиналық оқыту әдістерін қолдану және болжамның дәлдігін арттыруға мүмкіндік беретін балама деректер көздерін пайдалану мәселелері қарастырылады. Әртүрлі несиелік өнімдерге байланысты талдау скорингтік карталарды құрудың оңтайлы тәсілін таңдауға ұсыныстар жасауға мүмкіндік береді. Бұл өз кезегінде қарыз алушының несиелік қабілетін болжаудың дәлдігін арттырып, дефолт тәуекелінің деңгейін төмендетеді.

Тірек сөздер: несиелік скоринг, скорингтік карталар, несиелік өнімдер, қайта қаржыландыру, машиналық оқыту, тәуекелдерді басқару, несиелік қабілеттілік, балама деректер.

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СКОРИНГОВЫЕ КАРТЫ ДЛЯ РАЗЛИЧНЫХ ТИПОВ КРЕДИТНЫХ ПРОДУКТОВ

Аннотация

Развитие кредитного скоринга является одной из ключевых тем, на которые обращают внимание при управлении кредитными рисками в финансовых компаниях. Однако единый подход к созданию рейтинговых карт зачастую бесполезен, поскольку кредитные продукты различаются по уровню риска и срокам финансирования, а информации о заемщиках зачастую недостаточно. В статье рассматриваются особенности создания кредитных карт для потребительского кредитования, рефинансирования, малого и среднего бизнеса, автокредитования, ипотечного кредитования, финтеха и P2P-кредитования. Таким образом, настоящую работу можно рассматривать как приведенный выше сравнительный анализ наиболее важных элементов, влияющих на вероятность дефолта заемщика при расчетах по сегментам, вместе с рассмотрением методов машинного обучения и использованием альтернативных источников данных, которые могут повысить точность прогноза. В зависимости от обычного кредитного продукта анализ позволяет выработать рекомендации по выбору оптимального подхода к созданию скоринговых карт, что повышает точность прогнозирования кредитоспособности заемщика и снижает степень риска дефолта.

Ключевые слова: кредитный скоринг, скоринговые карты, кредитные продукты, рефинансирование, машинное обучение, управление рисками, кредитоспособность, альтернативные данные.

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