Leveraging Network Topology for Credit Risk Assessment in P2P Lending: A Comparative Study under the Lens of Machine Learning

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Introduction to P2P Lending - Overview

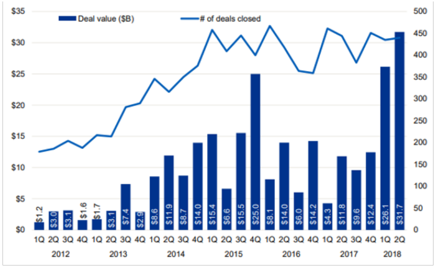
The emergence of FINTECH

Digital innovation brought major improvements in connectivity of systems, computing power, storage, newly created and usable data which in turn lead to the emergence of many new business models and entrants.

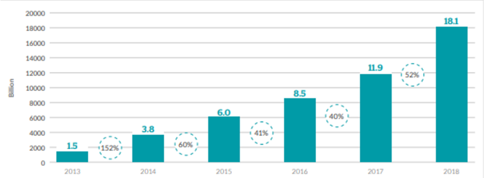
Fintech Credit

All credit activity facilitated by platforms that match borrowers with lenders (FSB, 2020).

Global investment activity in fintech companies



European Online Alternative Finance Market Volumes 2013-2018 in € billions (Including the UK)



Advantages of P2P Lending Platforms

An Overview

Peer-to-peer (P2P) lending platforms have reshaped the financial landscape, removing traditional financial intermediaries.

Micro Perspective

Accessibility: Simplified loan access for individuals without strigent credit checks.

Potential Returns: Can offers higher returns for investors.

Flexibility: More customizable loan terms based on borrower needs.

Macro Perspective

Economic Growth: Stimulates economy through capital flow.

Financial Inclusion: Serves borrowers in areas that are underserved by banks.

Innovation: Disrupts traditional banking and lending, thus driving innovation.

Disadvantages of P2P Lending Platforms

An Overview

While beneficial, P2P lending platforms also have drawbacks and risks for lenders and borrowers.

Micro Perspective

Credit Risk: Higher default risk due to relaxed credit checks.

Limited Insurance: Most P2P loans are uninsured, increasing risk for lenders.

Liquidity Risk: Difficulty in withdrawing investment before loan matures if no buyback guarantee established.

Macro Perspective

Regulatory Uncertainty: New financial model with sparse regulatory frameworks.

Systemic Risk: With platform growth the systemic risk component increases.

Uneven Market: May exacerbate inequality by favoring certain demographic groups.

Risk Ownership

Overview

A critical difference between traditional financial intermediation and P2P lending systems is the nature of risk ownership, which carries distinct implications for the accumulation of bad debt.

Traditional Lending

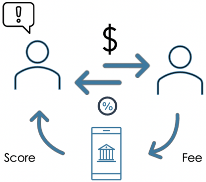
Risk Ownership: The institution (bank) that provides the credit score also takes on the risk of the loan defaulting.

Incentives: Banks have an inherent interest in providing accurate credit scoring due to the direct risk they bear.

P2P Lending

Risk Ownership: The platform provides the credit score, but the credit risk is borne by the investors.

Incentives: The platform's primary interest lies in increasing lending volumes, which may compromise the accuracy of credit



P2P Lending and Network-Based Modeling - Network-based Approach to P2P Lending

Overview

We apply a network-based modelling approach because it allows us to visualize relationships among borrowers and lenders, which is particularly relevant in the context of P2P lending through its decentralized nature and publicly available credit information.

Key Components

- **Nodes:** Represent individual borrowers and lenders.
- **Edges:** Represent lending transactions or relationships.
- **Weights:** Can represent the size of loans, interest rates, or default probabilities.

Advantages

- Captures complex interdependencies and contagion effects, providing understanding of risk dynamics in a decentralized lending environment.
- The approach also facilitates the assessment of network centrality that could help in evaluating risk dynamics within P2P lending.
- Enables the identification of key nodes (borrowers/lenders) and potential hotspots of credit risk.

Research Motivation

Overlooking Network Structures

We see it critical to overlook intricate network structures inherent in P2P lending platforms.

The relative importance of various risk factors in predicting loan defaults is a topic of ongoing debate that triggers our research.

Innovative Modelling Technique

Our study is motivated to invent an advanced machine learning method to improve the accuracy of credit scoring in P2P lending.

We investigate if incorporating information on the interconnections between borrowers can improve the predictive utility of scoring models.

Incorporating Graph Theory-Based Features

We do this by:

- Integrating graph theory-based features with conventional credit risk factors to enhance the prediction accuracy.

- Capturing the network structure of P2P lending platforms in terms of lender/borrower clustering.

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Literature Review: Network Models and Risk Estimation

The relevance of network models in risk assessment and loan default prediction within complex financial systems is increasingly recognized *(Allen et al. 2009; Angelini et al. 2008; Battiston et al. 2012)*.

Previous research also utilized machine learning, including neural networks, to predict consumer credit risk and default, demonstrating superior performance compared to traditional methods *(Khandani, Kim, and Lo 2010; Berg et al. 2020)*.

In P2P lending, network models have recently been adopted, granting improved accuracy in default prediction under the use of topological information *(Giudici and Hadji-Misheva 2019)* and the incorporation of network centrality features *(Giudici, Hadji-Misheva, and Spelta 2020)*. Scholars recently further utilized network effects for loan default prediction thereby extrapolating the importance of network centrality in risk estimation. *(Chen et al. 2022a,b)*.

There are still numerous uncharted areas in the incorporation of network models in credit risk modeling, which presents unique opportunities for future research.

Contribution of the Study

Study Context

Our study contributes to the field of P2P lending by integrating traditional credit risk factors with graph theory-based features for more accurate loan default prediction.

Two-Step Machine Learning Methodology

We introduce an enhanced two-step machine learning methodology that improves prediction accuracy and offers practical insights for effective risk management and decision-making.

Comparative Evaluation

Our research provides a comparative analysis of various machine learning techniques. This guides practitioners in model selection for specific needs, contributing to the discourse on effective machine learning in finance.

Laying Ground for Future Research

Our findings provide a stepping stone for future research in exploring additional informative features, alternative machine learning models, and extending the methodology to other financial domains.

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Bondora: A Leading European Peer-to-Peer Lending Platform

Overview

Bondora (https://www.bondora.com/en) is a peer-to-peer (P2P) lending platform established in Estonia. The platform's operational design allows lenders and borrowers to transact directly between each other.

Diverse Participant Base

- Bondora boasts a diverse user base, encompassing 225,837 individual lenders.
- Lenders lend funds to borrowers with varied demographic and credit backgrounds.

Rich Data

- The platform has issued €867.5 Mio. in loans and is operating in Estonia, Finland, Spain, and Slovakia.
- It offers rich data on loan listings, bidding records, and payment histories.

Data Set Characteristics

Dataset Details

Our study leverages a dataset of 32,469 individual loans before the data pre-processing steps. Within the loan sample 12,228 loans are defaulted and 20,241 are non-defaulted loans.

Variables and Metrics

The dataset includes 155 variables relating to the borrower's demographics, financial history, and loan characteristics.

Of these variables the most informative features are 'liab.1', 'inc.total', 'MonthlyPayment', 'log.amount', 'time', 'Interest', 'Amt. of Prev. Loans Bef. Loan', 'No. Prev. Loans', and 'Age'.

Descriptive Statistics of the Most Informative Loan Features on the Cleaned, Unbalanced Data Set

Table 3: Descriptive Statistics for Informative Loan Features on the Cleaned, Unbalanced Data Set

	liab.l	inc.total	Monthly Payment	log. amount	time	Interest	Amt. Prev. Loans Bef. Loan	No. Prev. Loans	Age
Observations	32469.00	32469.00	32469.00	32469.00	32469.00	32469.00	32469.00	32469.00	32469.00
Mean	5.11	6.98	4.03	7.28	3.55	17.76	5317.28	2.71	39.63
Std. Dev.	2.08	0.53	0.97	0.92	0.64	5.39	6034.19	3.02	11.46
Min	0.00	0.79	0.00	4.66	1.84	7.27	0.00	0.00	18.00
Max	10.48	13.09	7.55	9.27	4.80	38.00	74740.00	26.00	70.00

Notes: This table presents the summary statistics of the most informative loan features on the cleaned, unbalanced data set.

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Data Preprocessing

Cleaned the data by:

- Dropping rows with missing values.
- Removing unnecessary date columns and irrelevant variables.
- Removing forward-looking biased variables, like "return", "RR1", and "FVCI".
- Handling dummy variables.
- Dealing with multicollinearity by checking the correlation matrix and dropping columns with a correlation greater than 0.95.

Created a balanced sample, ensuring an equal number of instances for each class:

- Randomly selecting 5000 observations from default loans and 5000 observations from non-default loans to create a balanced data set.

Two-step Model: Step 1 - Build a Graph on Data

An Explanation

Graph theory offers a robust framework for analyzing complex relational data, including financial networks. These networks encapsulate financial entities as nodes and relationships as edges, providing valuable insights into risk dynamics *(Biggs, Lloyd, and Wilson 1986; Newman 2010; DeMarzo 2003)*.

Key Concepts

- **Graph:** A set of nodes (vertices) and edges (links).
- **Degree:** Number of edges connected to a node.
- **Path:** Sequence of nodes in which each node is connected to the next by an edge.
- **Cycle:** Path whose first and last nodes are the same.

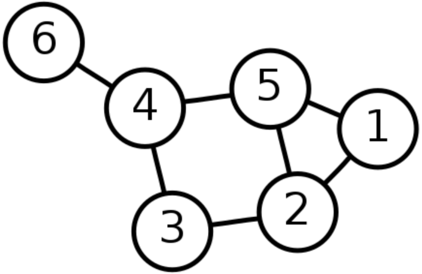


Figure: An example of graph

Two-Step Model: Step 1 - Build a Graph on Data

Overview

Centrality measures are important tools in network analysis, used to identify the most important nodes within a network. In the context of P2P lending, these nodes could represent key borrowers or lenders.

Key Measures

- **Degree Centrality:** Number of connections a node has.
- **Closeness Centrality:** How fast information can spread from a given node to other reachable nodes in the network.
- **Betweenness Centrality:** A node's centrality.
- **Eigenvector Centrality:** A node is considered important if it is connected to other important nodes.

Mathematical Formulation

- Formula for Degree Centrality: $C_D(v) = \deg(v)$
- Formula for Closeness Centrality: $C(x) = \frac{1}{\sum_y d(y,x)}$
- Formula for Betweenness Centrality: $C_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)}$
- Formula for Eigenvector Centrality: $PR(p) = (1-d) + d \sum_{i \in M(p)} \frac{PR(i)}{L(i)}$

Two-Step Model: Step 1 - Build a Graph on Data (cont.)

Overview

Other centrality measures like Katz Centrality, Hub Centrality, and PageRank could provide valuable insights about key participants in P2P lending.

Additional Measures

- **PageRank:** More important websites are likely to receive more links from other websites.
- **Katz Centrality:** Takes into account the total number of walks between a node and all others.
- **Hub Centrality (HITS):** The HITS (Hyperlink-Induced-Topic-Search) algorithm is an analysis tool to rate links between nodes.

Mathematical Formulation

- Formula for PageRank:
  $PR(p) = (1-d) + d \sum_{i \in M(p)} \frac{PR(i)}{L(i)}$
- Formula for Katz Centrality:
  $C_{\text{Katz}}(i) = \sum_{j=1}^{n} \beta A_{ij} C_{\text{Katz}}(j) + \alpha$
- Formulas for Hub Centrality (HITS):
  - Authority Score: $a(i) = \sum_{j \in M(i)} h(j)$
  - Hub Score: $h(i) = \sum_{j \in N(i)} a(j)$

Significance

Centrality measures can identify potential hotspots of credit risk in P2P lending.

Two-Step Model: Step 2 - Supervised Models based on Graph Features

Introduction to Elastic Net

The Elastic Net Logistic Regression model integrates the strengths of both L1 (Lasso) and L2 (Ridge) penalties, providing an effective balance between bias and variance to ensure model generalizability.

Model Implementation

$$\beta = \arg\min_{\beta} \left(\frac{1}{2}||y - X\beta||_2^2 + \lambda((1-\alpha)||\beta||_2^2 + \alpha||\beta||_1) \right)$$

Here, $||\cdot||_2$ is the L2 norm, $||\cdot||_1$ is the L1 norm, λ is the regularization parameter, and α is the mixing parameter that ranges between 0 and 1.

Model Configuration

The alpha and lambda parameters are varied, with alpha ranging from 0 (Ridge penalty) to 1 (Lasso penalty) and $\lambda \in [1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100]$, enabling different degrees of regularization and feature selection.

Two-Step Model: Step 2 - Supervised Models based on Graph Features

Introduction to Random Forest

Random Forests, due to their nonparametric nature, are effective in handling high-dimensional spaces and complex interactions, making them a strong tool for default prediction in credit risk modeling.

Model Implementation

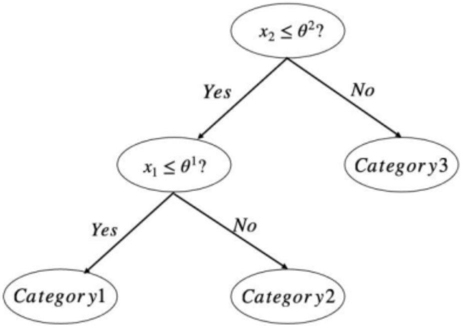


Figure: A decision tree

Model Configuration

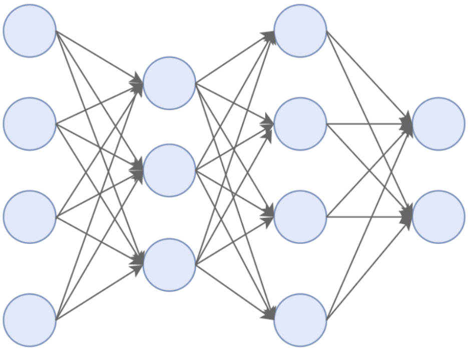
The model is configured with varying 'ntrees' (50-250) and 'max-depth' (5-20), to explore and determine the most suitable model configuration for the dataset in use.

Two-Step Model: Step 2 - Supervised Models based on Graph Features

Introduction to Deep Neural Network

Deep learning methods such as Multi-Layer Perceptron (MLP) enable models to automatically learn representations of data through neural networks with multiple layers, accommodating the complexity of credit risk data *(LeCun 2015)*.

Model Implementation



Model Configuration

The model consists of various configurations of hidden layers, using the rectified linear unit (ReLU) activation function. The hyperparameter 'epochs' denotes the number of complete passes through the entire training dataset.

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Models Description and Representation

In our study, we utilized six different models. These models were differentiated based on the types of features they incorporated:

Model 1: Initial features (informative and uninformative). Python representation: .

Model 2: Initial features (informative and uninformative), and graph features. Python representation: .

Model 3: Only initial features (informative). Python representation: .

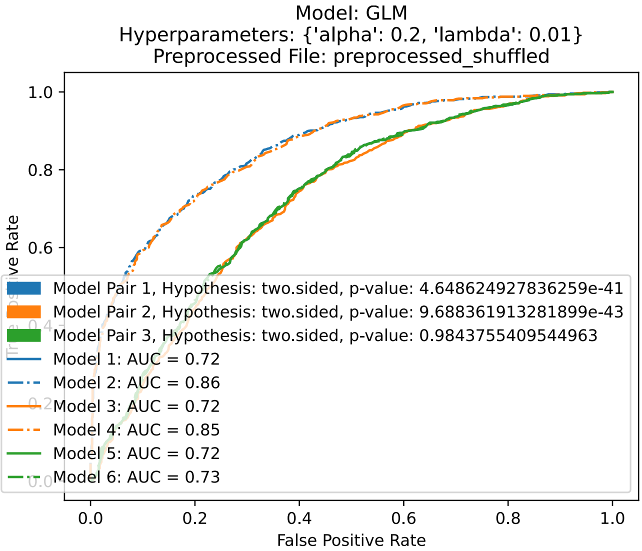
Model 4: Initial features (informative), and graph features. Python representation: .

Model 5: Initial features (informative and uninformative). Python representation: .

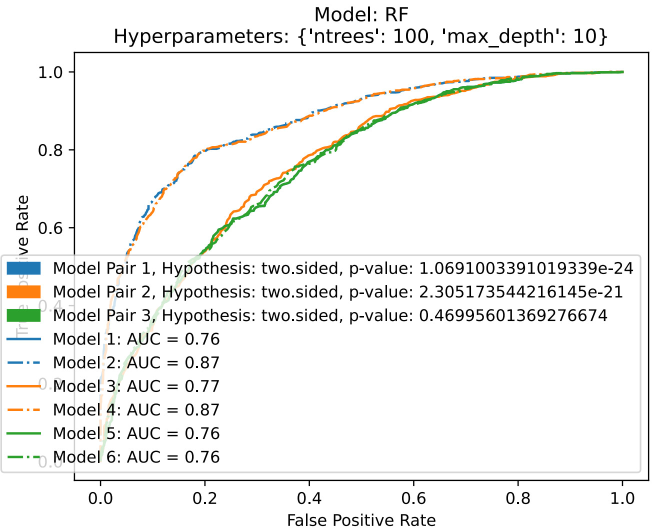
Model 6: Initial features (informative and uninformative), and shuffled graph features. Python representation: .

Each model is represented in Python using a specific color and linestyle.

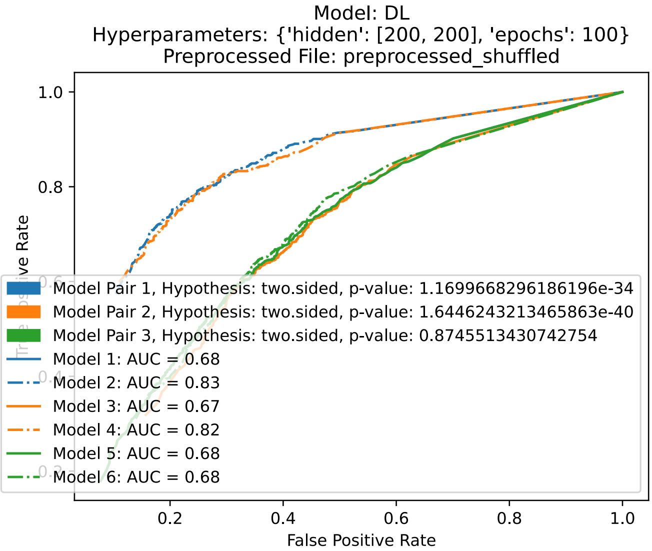
ROC and AUC: GLM



ROC and AUC: RF



ROC and AUC: DL



Feature Importance: GLM

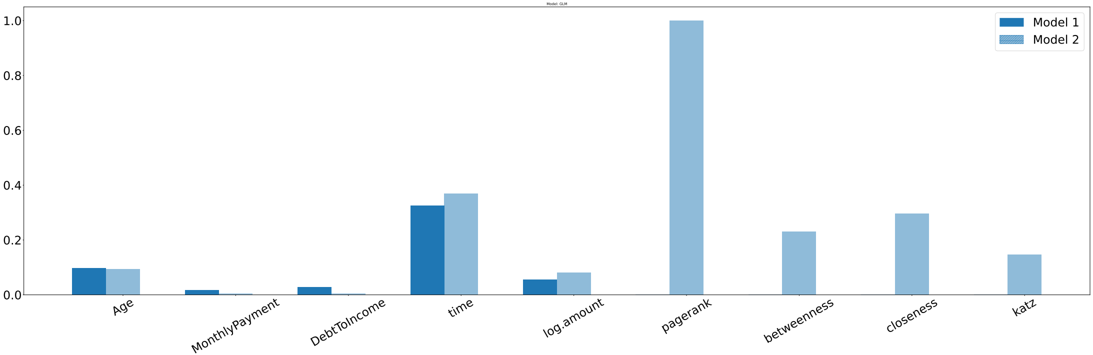


Figure: Feature Importance for Generalized Linear Model (GLM)

Feature Importance: RF

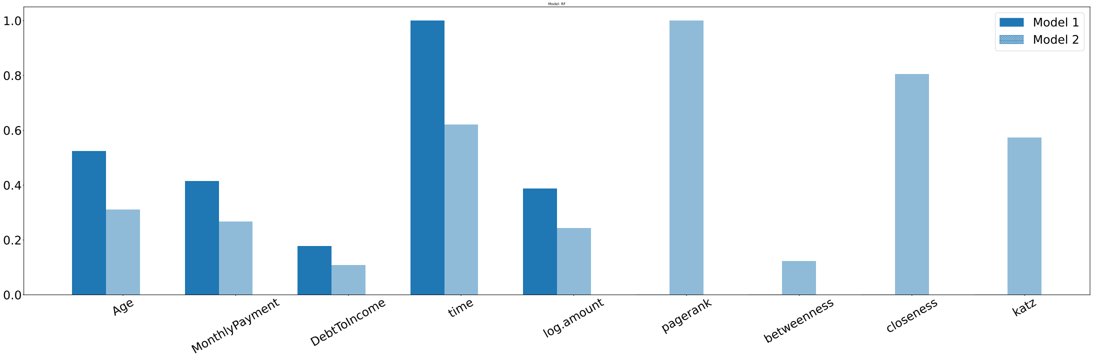


Figure: Feature Importance for Random Forest (RF)

Feature Importance: DL

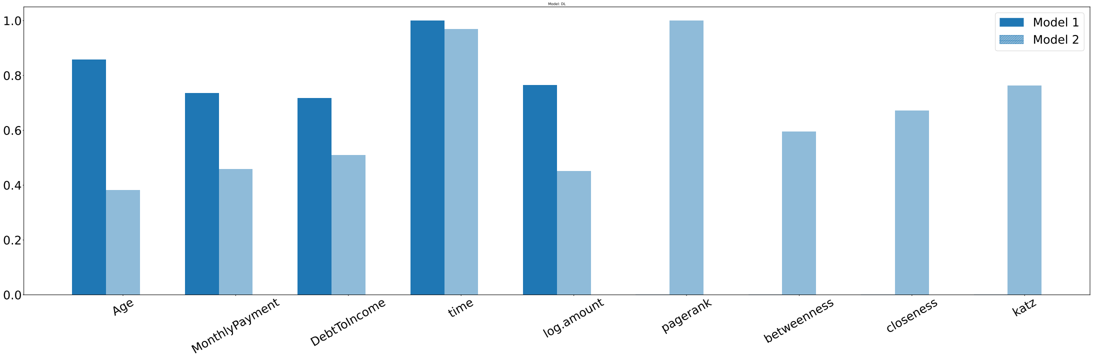


Figure: Feature Importance for Deep Learning Neural Network (DL)

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Understanding Credit Risk - Types of Credit Risks

Overview

Credit risk can be classified into various types, each with distinct characteristics and implications for lenders and borrowers.

Default Risk

- Risk of borrower failing to repay the loan
- Quantified by default probability
- Central to credit risk modeling

Concentration Risk

- Risk arising from a lack of diversification
- Can result from exposure to a single borrower or sector
- Mitigated through diversification strategies

Systemic Risk

- Risk of widespread defaults impacting the entire financial system
- Can result from network effects or contagion
- Difficult to mitigate, often requires regulatory measures

Significance

Understanding the different types of credit risks is essential for effective risk management in P2P lending markets. Identifying and managing these risks can help maintain the stability and sustainability of the market.

Understanding Credit Risk - Basic Principles

Definition

Credit risk is the risk of loss due to a borrower's failure to make payments on any type of debt.

Key Elements

- Default probability: The likelihood of a borrower not meeting debt obligations.
- Exposure at default: The total value a lender is exposed to at the time of default.
- Loss given default: The proportion of the exposure that will be lost if a default occurs.

Mathematical Formulation

- Credit risk is often quantified as Expected Loss (EL), which is a product of the before mentioned elements: $EL = PD * EAD * LGD$
- Each of these elements can be estimated using various statistical and mathematical models.

Understanding Credit Risk - Credit Scoring and Rating

Definition

Credit scoring and rating are systematic approaches used by lenders to assess the creditworthiness of borrowers, involving a variety of statistical and mathematical techniques.

Credit Scoring

- Quantitative method for predicting default risk by using statistical models like logistic regression
- Produces a numerical score representing creditworthiness

Credit Rating

- More comprehensive, includes qualitative factors
- Often used for firms, sovereign states, or specific securities
- Results in a rating class, e.g., AAA, AA, A, BBB, etc.

Credit Risk Models in P2P Lending - Introduction to Network-Based Credit Risk Models

Overview

Network-based credit risk models capture the interconnectedness in financial systems and can provide a more comprehensive understanding of systemic risk in P2P lending markets.

Key Concepts

- **Network Representation:** Borrowers and lenders are represented as nodes, and credit relationships as edges.
- **Systemic Risk:** Risk of default can spread through the network due to interconnected exposures.
- **Centrality Measures:** Nodes with high centrality can play significant roles in spreading risk.

Advantages over Conventional Models

- Capturing contagion effects within clustered networks.
- Incorporating network structure in risk assessment.
- Identifying key nodes based relative position in the network with implications for borrowing dynamics.

Significance

Network-based credit risk models offer a powerful tool for understanding and managing credit risk in P2P lending markets, particularly due to their ability to capture systemic risk and contagion effects.

Two-step Model: Step 1 - Build a Graph on Data

Overview

Conventional credit risk models are primarily based on individual borrower's characteristics and financial health, often ignoring the networked nature of credit risk in P2P lending.

Key Models

- **Credit Scoring Models:** Use borrower data (credit history, income, etc.) to assign credit scores.
- **Structural Models:** Based on firm's asset value and its volatility.
- **Reduced Form Models:** Use statistical or machine learning methods to predict default probabilities.

Limitations in P2P Context

- Lack of comprehensive borrower data.
- Inadequate for capturing network effects.
- Limited ability to capture systemic risk.

Significance

While traditional models provide a starting point, the unique characteristics of P2P lending require the development of novel, network-based credit risk models that can effectively capture the systemic nature of credit risk in these markets.

Credit Risk Models in P2P Lending - Strengths and Limitations of Network-Based Models

Overview

While network-based models provide unique insights into systemic credit risk, they also come with certain limitations that need to be acknowledged for effective application in P2P lending markets.

Strengths

Systemic Risk: Can capture systemic risk and contagion effects.

Network Structure: Incorporates network structure in risk assessment.

Identification: Identifies key nodes influencing systemic risk.

Limitations

Data Requirements: Requires detailed network data, which might not always be available.

Computational Complexity: Can be computationally intensive for large networks.

Model Assumptions: Based on certain assumptions (e.g., network structure, default correlations) that may not hold in all scenarios.

Significance

Understanding the strengths and limitations of network-based models is crucial for their effective application in credit risk assessment and management in P2P lending markets.

Understanding Centrality Measures

Overview

Centrality measures are techniques used in network analysis to identify the most important nodes in a network. There are several types, each with distinct characteristics and computational formulas.

Degree Centrality

- Number of edges connected to a node
- In directed networks, distinguishes between in-degree and out-degree centralities
- Formula for undirected graph: $C_D(v) = \deg(v)$

Closeness Centrality

- Measures speed of information spread from a given node to others
- Formula: $C(x) = \frac{1}{\sum_y d(y,x)}$

Betweenness Centrality

- Number of shortest paths from all vertices to all others passing through the node
- Formula: $C_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)}$

Reference

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Understanding Centrality Measures (Continued)

Overview

We continue to discuss other important centrality measures such as Eigenvector Centrality and PageRank. These measures highlight the importance of nodes based on their connections and influence in the network.

Eigenvector Centrality

- Importance of a node if it is connected to other important nodes
- Iteratively calculated, based on the centrality of the neighboring nodes
- Formula: $C_E(v) = \frac{1}{\lambda} \sum_{t \in M(v)} C_E(t)$

PageRank

- Algorithm to rank web pages in search engine results
- Counts the number and quality of links to a page
- Formula: $PR(p) = (1 - d) + d \sum_{i \in M(p)} \frac{PR(i)}{L(i)}$

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Bonacich, P. (1987). Power and centrality: A family of measures. American journal of sociology, 92(5), 1170-1182.
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Understanding Further Centrality Measures

Overview

Katz Centrality and HITS Algorithm (Hub and Authority scores) offer unique perspectives on node importance in a network. Their formulations consider both direct and indirect influence in the network.

Katz Centrality

- Considers both the direct and indirect influence of a node's neighbors
- Iteratively calculated, based on the centrality of the neighboring nodes
- Formula: $C_{\text{Katz}}(i) = \sum_{j=1}^{n} \beta A_{ij} C_{\text{Katz}}(j) + \alpha$

HITS Algorithm (Hub and Authority scores)

- Each node has two scores: an authority score and a hub score
- Calculated iteratively until convergence
- Formulas:
  - Authority Score: $a(i) = \sum_{j \in M(i)} h(j)$
  - Hub Score: $h(i) = \sum_{j \in N(i)} a(j)$

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Histogramms of Most Important Loan Features

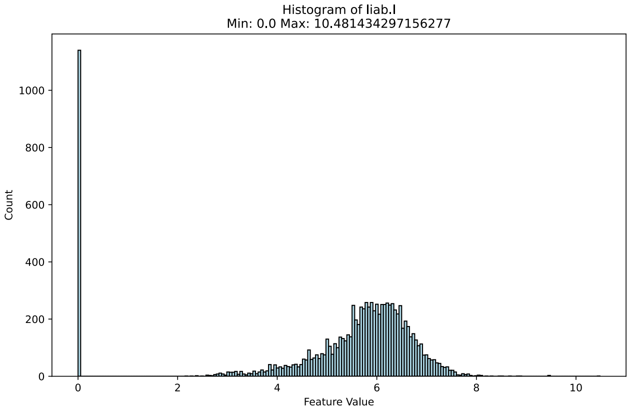

Figure: Histogramm of loan feature liab.l

Histogramms of Most Important Loan Features

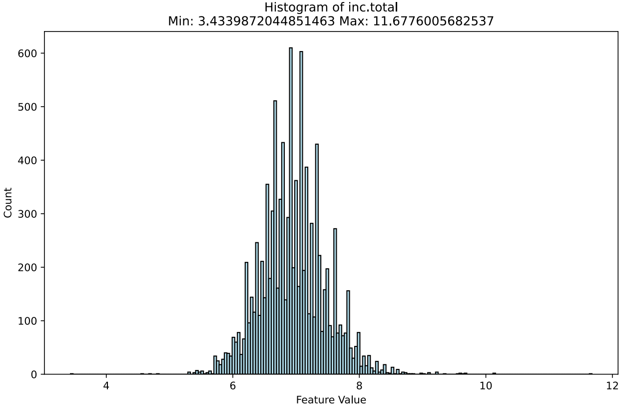

Figure: Histogramm of loan feature inc.total

Histogramms of Most Important Loan Features

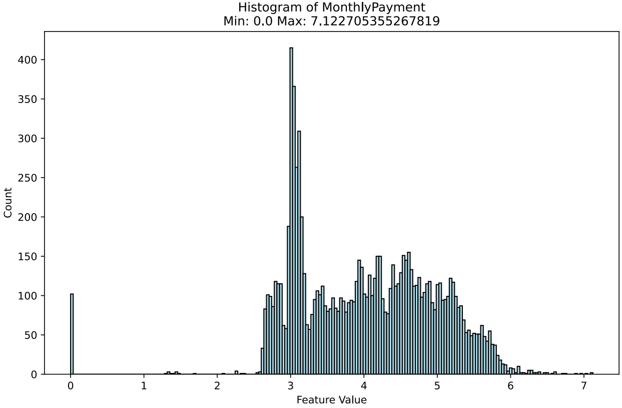

Figure: Histogramm of loan feature MonthlyPayment

Histogramms of Most Important Loan Features

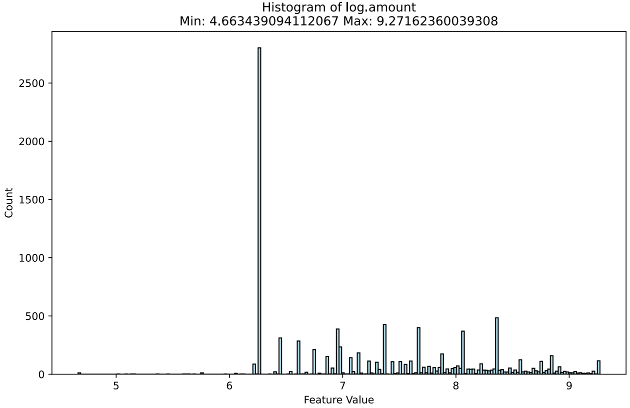

Figure: Histogramm of loan feature log.amount

Histogramms of Most Important Loan Features

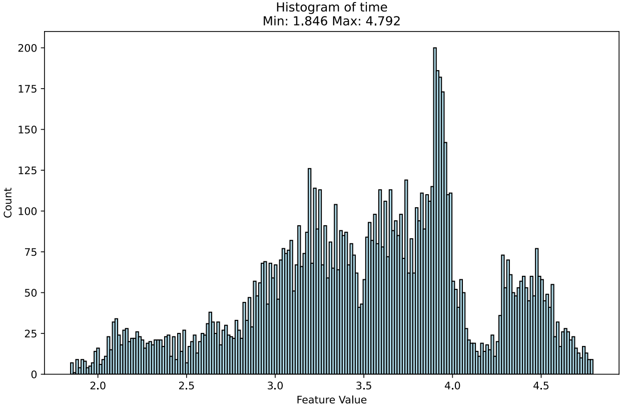

Figure: Histogramm of loan feature time

Histogramms of Most Important Loan Features

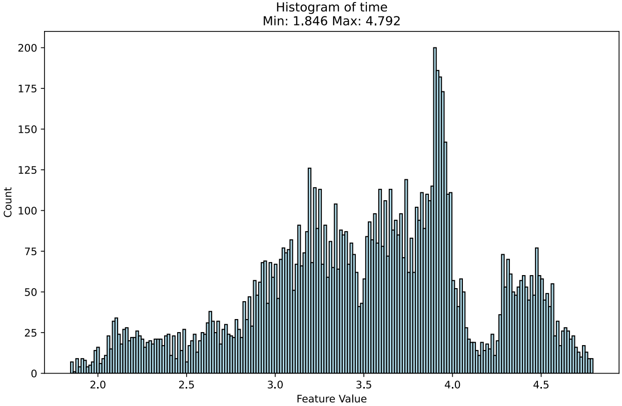

Figure: Histogramm of loan feature time

Histogramms of Most Important Loan Features

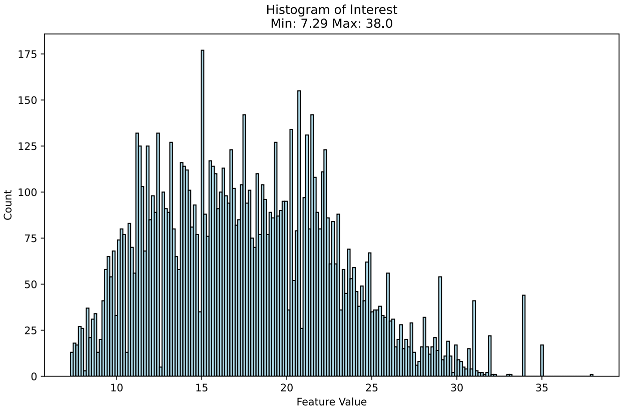

Figure: Histogramm of loan feature interest

Histogramms of Most Important Loan Features

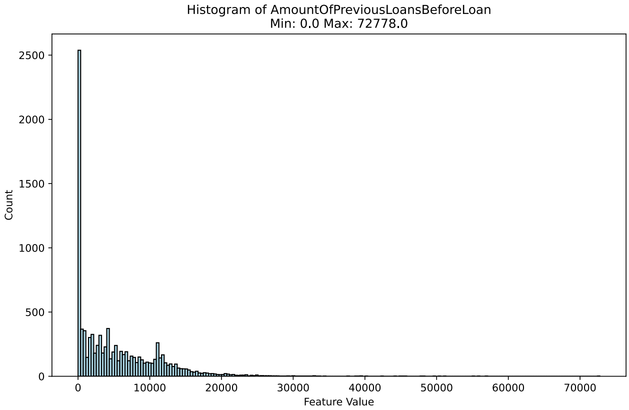

Figure: Histogramm of loan feature Amt. of Prev. Loans Bef. Loan

Histogramms of Most Important Loan Features

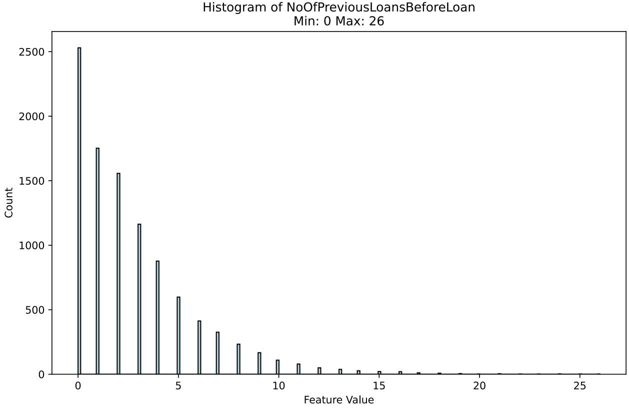

Figure: Histogramm of loan feature No. Prev. Loans

Histogramms of Most Important Loan Features

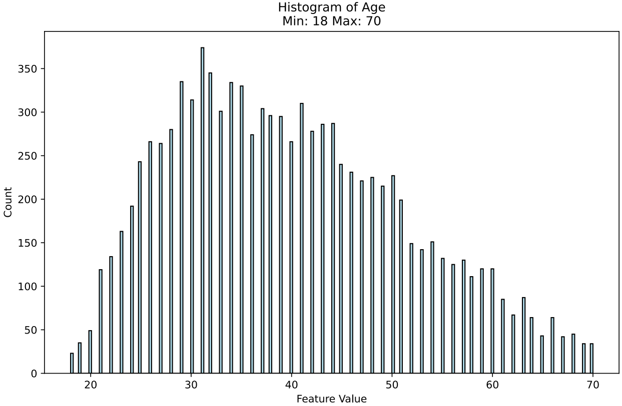

Figure: Histogramm of loan feature Age