A Bayesian Approach to Generating Optimal Loan Structures

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***Abstract*—The inherent risks in commercial and personal lending, particularly in developing countries, pose significant challenges due to potential borrower defaults and complex financial landscapes. This research addresses these issues by employing Bayesian Networks to create loan structures that minimise risk for lenders while offering viable financing options for borrowers. By making use of score-based structure learning, Bayesian estimation and MAP inference, the most probable loan structures for a given borrower are identified. Our experiments demonstrate that structure learning approaches, specifically the Bayesian Information Criterion (BIC), K2, and BDs algorithms, consistently outperform random and tree-based methods across various dataset sizes. Additionally, the findings indicate that more detailed evidence lists enhance model performance. This research contributes a transparent and interpretable machine learning framework for financial decision-making, ultimately improving the lending process for both lenders and borrowers.**

***Index Terms*—Bayesian Networks, ExplainableAI, Probabilistic Graphical Models, Machine Learning, Consumer Lending, Intelligent data, and probabilistic inference**

I. Introduction

COMMERCIAL and consumer lending, including loans to small and medium-sized enterprises (SMEs), carries significant risk due to the potential for borrower default. SMEs in developing countries face specific challenges, including difficulty accessing financing due to the lack of audited financial statements and collateral [1], [2]. Another challenge is being charged higher interest rates and fees compared to those in developed countries, which increase their repayment burden and default risk [1], [2]. A key challenge faced by lenders in these countries is that banks experience higher rates of non-performing loans from their small and medium-sized enterprise (SME) lending. This challenge is further exacerbated by the broader macroeconomic environment [1].

The above discussion gives light to the importance of creating a loan structure that could potentially minimise risk for lenders and challenges for borrowers. The problem of creating a loan structure that achieves this involves taking into account information about the borrower, which is shown in the idea of risk-based pricing [3]. Therefore, creating a loan structure tailored to a specific borrower, would minimise the above mentioned risks and challenges. The creation of this tailored loan structure for a specific borrower, therefore becomes the main problem focus.

Previous literature has addressed modelling individual components of a loan, such as interest rates and credit risk. These include both traditional and machine learning (ML) approaches [4], [5], [6] [7] [8]. The literature on ML mainly focuses on modelling credit risk, with some of these techniques being black-box and unexplainable [9].

This research aims to provide an explainable ML method to create a suitable loan structure that is tailored towards a specific borrower. This proposed method will model the loan structure and the associated components holistically aiming to address the problem statement above.

To achieve this, we will construct a Bayesian Network (BN), in which the structure and parameters will be learnt from data. This BN will be used to predict the most probable values of the different components of a loan structure. Borrower specific financial information will be used as evidence to infer these values. Various amounts of borrower information will be used to assess the effect on the model's ability to predict the most suitable loan structure. The proposed BN will be compared to two different benchmarks, these representing methods that are similar to the methods commonly known to be used in industry.

Through the experiments, our proposed Bayesian Network (BN) model was found to fit the loan data better than the two benchmark models, as shown by higher log-likelihood scores. The proposed BN also produced more probable loan structure predictions than the benchmarks, particularly when more borrower information was provided. Additionally, the proposed model outperformed the benchmarks even when it had access to less borrower information than the benchmarks.

This research introduces an explainable and transparent machine learning framework for generating tailored loan structures for individual borrowers. Unlike methods that solely predict borrower credit risk, this approach enables the prediction of multiple loan components, providing a more comprehensive and personalised loan structure.

The report proceeds with a review of related work, discussing relevant literature and previous research on similar problem areas. The methodology section details the steps taken to develop and evaluate the proposed method, including the data preparation, model construction, and evaluation approach. In the results section, findings are presented and analysed to assess model performance. Finally, the discussion and conclusion sections interpret the findings in a broader context, summarising the contributions and limitations of this research.

II. Related Work

This section will consist of a Conceptual Framework, in which the variables relating to the problem statement will be discussed. Next, the Solutions section will discuss the various ways in which the problem statement has been addressed. Within this Solution section, the traditional, general ML and Bayesian Network methods used will be discussed.

A. Conceptual Framework

The structure and pricing of loans are shaped by various factors, including interest rates, loan terms, amounts, repayment schedules, and credit risk. Interest rates function both as a cost to the borrower and a source of profit for banks [10]. Loan terms influence the duration of interest income and the management of asset financing, while the loan amount affects bank profitability and exposure to potential losses from defaults. Repayment schedules play a crucial role in balancing borrower cash flow and lender risk [11].

Risk-based pricing adjusts loan interest rates according to the borrower's credit risk [3]. Collateral, on the other hand, mitigates lender risk and can lower borrowing costs [12]. Additionally, macroeconomic factors such as GDP growth, interest rate fluctuations, and unemployment rates significantly influence credit risk [13].

To evaluate a borrower's creditworthiness, the "5 C's of Credit" framework—Character, Capacity, Capital, Collateral, and Conditions—is widely used [14].

B. Solutions

While there is limited literature on methods for creating a comprehensive loan structure, existing research focuses on specific components of loan structuring.

1) Traditional Methods: There are various traditional, non-machine learning methods to model interest rate, these methods include the risk-neutral approach, the Heath-Jarrow-Morton framework as well as additional models [4]. Similarly, various non-machine learning methods exist for modeling credit risk, including the structural approach, intensity-based approach, hybrid models, Copula-based approaches, and term structure modeling approaches [5].

2) Machine Learning Methods in Credit Risk Analysis: Various machine learning (ML) methods have been studied for credit risk prediction. Random forests were found to outperform other ML models in predicting loan defaults [8], while clustered support vector machines (CSVM) were highlighted for their computational efficiency and performance in credit risk analysis [15]. Neural networks have also been extensively used, with various approaches showing their effectiveness in default prediction [16], [17].

Despite their performance, all of the above mentioned ML techniques are often criticised in financial settings for their black-box nature [9]. Certain models needed and used post-hoc explainability techniques such as LIME, SHAP, and Quantitative Input Influence to provide explainability for their credit risk prediction [18], [6], [19].

The study of explainability and transparency in Artificial Intelligence (AI) and ML fall under the field of Explainable AI (XAI). XAI aims to design systems that provide clear details about their operations, making their functioning easily understandable [9]. Different ML models have different levels of explainability [9]. The risks of using non-transparent AI and ML models in finance have been emphasised, warning against the use of uninterpretable models to mitigate potential risks in financial markets [20].

3) Bayesian Network Methods in Credit Risk Analysis: Bayesian Networks (BNs) are seen to be transparent ML models and do not need post-hoc explainability techniques [9]. Multiple studies have explored the use of BNs in credit risk analysis, by estimating the probability of default [21], [22], [7], [23]. Credit expert knowledge was used to design the structure of certain models [23], whereas structure learning approaches were applied to develop others [21], [22]. The score-based structure learning approach, employing the Hill-Climbing algorithm with the K2 score, was applied [21]. The Chow-Liu algorithm was employed to learn the structure of the Tree Augmented Naive Bayes (TAN) model [22], and the minimal description length (MDL) score was used to select the best model [22]. Conversely, expert knowledge combined with the score-based Hill-Climbing algorithm was applied to construct the structure of a BN [7].

Different methods were used to learn the parameters for the BNs, namely Bayesian estimation with the Dirichlet prior [21], the Expectation Maximisation algorithm, [7] and using expert knowledge to estimate the parameters [23].

The studies employed diverse evaluation methods for their models, including: k-fold cross-validation [22], ROC curves [22], Kolmogorov-Smirnov testing [21], classification metrics [7], and analysis of model structure and complexity [23].

It was found that BNs outperform a logistic regression model [22], and are an effective and transparent technique to model credit risk [21], [23]. Bayesian Networks were also found to have the advantage to be able to integrate expert knowledge [23].

4) Other Noted Literature: Noting that credit risk is not the only factor to consider when constructing a loan structure, a study employed tree-based ensemble models to predict the take-up of home loan offers [24]. It was found that the increase in interest rate resulted in a decrease in take-up, and when the Loan to Value was high the take-up was high [24].

Through this literature review it was found that different factors are important when considering the construction of a loan structure. The ideas of credit risk, interest rate and risk-based pricing being the most notable. The literature demonstrates that while various ML techniques have been applied to credit risk modelling, their black-box nature limits their practical application in finance. Bayesian Networks offer a promising transparent alternative, with studies showing their effectiveness in credit risk assessment. However, current research primarily focuses on default probability alone, neglecting other crucial aspects of loan structuring. This gap suggests the need for a comprehensive BN-based framework that integrates multiple loan structure components while maintaining interpretability.

III. METHODOLOGY

The previous section reveals three key limitations in existing literature. Firstly, previous methods have focused on modelling individual components like credit risk or interest rates in isolation, rather than addressing loan structure holistically. Second, while many ML techniques have shown promising results, their black-box nature makes them unsuitable for financial applications where transparency is crucial. Third, while Bayesian Networks offer an explainable alternative, some approaches have relied exclusively on expert knowledge rather than learning from data, potentially limiting their ability to capture true underlying relationships in the data. This research aims to address these limitations by developing an explainable and interpretable BN that models the loan structure holistically.

This section outlines the complete pipeline for developing and evaluating our Bayesian Network approach. First, we present the specific research questions and experimental design. The cleaning and preprocessing of the data is described. To establish performance benchmarks, we develop two baseline models for comparison. We then construct several BN models through computational learning methods. These models will be used to predict loan structures based on borrower information. The models will be evaluated using the negative of the empirical log-loss.

A. Research Questions

1) How effective is a Bayesian Network in accurately predicting the a suitable loan structure for a given borrower, compared to industry standards, based on the total size of the dataset available?

In order to answer this question we constructed two baseline models and several BNs using various structure learning scores. Each model was trained on datasets of multiple sizes, ranging from smaller subsets to the full dataset, to examine how the amount of data available affects the models' performance. The metric used for evaluating the model's performance was the negative of the empirical log-loss (also known as the log-likelihood), and this was calculated for each model across all dataset sizes. This metric was compared for different dataset sizes to aid in answering our research question.

2) How does the availability of borrower-specific financial information (e.g., income, credit score) affect the ability of a Bayesian Network to accurately predict the most suitable loan structure (e.g., interest rate, loan term) for a given borrower compared to industry standards?

To address this research question, a similar approach to that used for the first question was applied, although the method for calculating the negative of the empirical log-loss was different. In order to assess the prediction of the suitable loan structure for a given borrower, the negative of the empirical log-loss was calculated using the joint probability.

The loan status was set to "Fully Paid" regardless of the borrower's actual status, aligning with the objective of identifying a suitable loan structure that minimises default risk. This assumption models a scenario in which the borrower successfully repays the loan under the proposed structure.

Borrower information was represented as evidence lists, each constructed from different subsets of features in the dataset. Four distinct evidence lists were created, each containing varying levels of borrower information. For each model, the negative of the empirical log-loss was calculated across these different evidence lists. By comparing this metric across the evidence lists, we aim to gain insights into how the amount of borrower information affects the model's ability to generate a suitable loan structure.

B. Data and Preprocessing

1) Study area: This research uses the Lending Club Loan data set, that was obtained from Kaggle [1]. LendingClub is an American lending company, and this data set consists of all of the loan data from this company. The dataset consists of records for both accepted and rejected loans. For this research we only use the data in which the loan was accepted, in order to get the data relevant to the loan structure and loan default.

The data consisted of 151 features and over 2 million records. This research uses 85 of the 151 features, and only 100,000 records. The features used for this research mainly consisted of those relating to the loan structure, the status of the loan and the borrower's financial information. Due to the large amount of features, only a subset of the features that are used in this research will be displayed in Table I. A data dictionary for this dataset can be found at: Lending Club Data Dictionary

TABLE I
TABLE OF A SUBSET OF SELECTED FEATURES

Feature	Description
Loan Amount	The amount of the loan issued to the borrower.
Term	The length of the loan.
Interest Rate	Interest rate on the loan.
Instalment	The monthly payment owed by the borrower
Grade	LendingClub assigned loan grade.
Employment Length	Employment length in years.
Home Ownership	The home ownership status of the borrower during registration.
Annual Income	The annual income provided by the borrower.
Loan Status	The status of the loan.
FICO High Range	The upper boundary range the borrower's FICO score at loan origination belongs to.
DTI	The borrower's debt to income ratio.
Earliest Credit Line	The month the borrower's earliest reported credit line was opened.

2) Data Preprocessing: This section will explain the various preprocessing steps that were taken, including data cleaning, feature selection and discretisation.

The dataset initially included irrelevant features that would have added unnecessary complexity, so these were removed. Since the dataset contained many missing values, removing all records with missing values would have led to a significant loss of information. To address this, we removed approximately 40 features that were largely incomplete, such as Settlement

[1] https://www.kaggle.com/datasets/wordsforthewise/lending-club/data

Term and various features relating to hardship, all of which had substantial missing data. Next, we removed features specifically related to co-borrowers. Since joint information of the co-borrowers was used, features such as Annual Joint Income were excluded to control complexity and due to high levels of missing data. The zip codes were excluded as they were censored in the dataset for privacy, rendering them uninformative.

A correlation heatmap (see Figure 6 in Appendix A) showed that certain features were highly correlated. To avoid redundancy and retain only the most informative features, we kept those most relevant to loan structuring, such as loan amount, while removing others such as funded amount, which were essentially equivalent.

To further clean the data, we removed the records where 83 out of 85 of the remaining features were missing or were NaN values.

To facilitate ease of use with Bayesian Networks, we discretised the data. Each feature was discretised individually based on it's nature: For instance, annual income was discretised using variable-sized bins, similar to tax bracket divisions. Most features were divided into five bins, with certain features having more or fewer bins depending on their specific characteristics. To address any remaining missing values, an "N/A" bin was added to each feature. When discretising Loan Status we excluded records where the loan status was not either fully paid or charged off.

The data cleaning process was conducted carefully to minimise unnecessary removal of records from the minority class. Since the dataset was significantly imbalanced, with "Charged Off" loans representing only about 25% of the "Fully Paid" records, it was essential to preserve minority-class records. After the data preprocessing, the data imbalance improved slightly with the "Charged Off" loans representing around 29% of the "Fully Paid" loans.

The loan structure features that will be predicted consist of: interest rate, term, instalment and loan amount.

The evidence lists containing borrower information were constructed through careful feature selection. These evidence lists consisted of features that represented the borrower's financial information. Four evidence lists of increasing sizes were created, with each list expanding on the previous one by incorporating additional features. These lists being: Very Basic, Basic, Detailed and Advanced. The criteria in which features were assigned to the lists was a) how directly related the feature is to credit risk and loan structure, and b) how accessible the information of the feature is. Knowledge gained through constructing the Related Work (section II), specifically the "5 C's of Credit" [14] from the Conceptual Framework (section II-A), was used to assess the features against the first criteria. For the second criteria, we assessed the nature of the feature to decide how accessible the information would be.

The very basic list consisted of annual income, employment length, grade, verification status, FICO high range, purpose, DTI, home ownership, total current account balance and public recorded bankruptcies.

The basic list contained the very basic features extended with last recorded FICO high range, application type, delinquencies for the past 2 years, average current account balance, number of mortgage accounts, number of instalment accounts, number of revolving accounts and total credit balance excluding mortgage.

The detailed list contained the basic features extended with total credit revolving balance, number of active revolving trades, number of open revolving trades, maximum current balance owed on revolving accounts, total revolving account limit, total current balance of instalment accounts, number of open credit lines, total number of currently open credit lines, number of tax liens, number of derogatory public records, number of bankcard accounts, earliest credit line, percent of trades never delinquent and number of accounts delinquent.

The advanced list contained the detailed features extended by revolving credit utilisation, all credit utilisation, bankcard utilisation, number of finance trades, total bankcard credit limit, number active bankcard accounts, number of satisfactory bankcard accounts, percent of bankcards greater than 75% of limit, number of accounts 30 days past due, number of accounts 90+ days past due, number of accounts 120+ days past due and number of accounts ever 120+ past due.

C. Benchmarks

A Chow-Liu TAN will be used as it is based off of industry standards [25] and a random BN will also be used as a lower bound of performance.

The random Bayesian Network represents a model that disregards meaningful associations between features, while still learning it's parameters from the data.

The Chow-Liu TAN is used as a benchmark for two reasons, the first being that this model was used in existing literature in credit risk analysis [22] [23]. The second reason stems from the Chow-Liu TAN being based off of a decision tree, which is used industry for credit risk and scoring [25]. The Chow-Liu TAN was chosen over a standard decision tree because it supports Bayesian inference, allowing for explainability as a Bayesian model [9].

D. Methods

Three different models are proposed to identify the best model for generating the most suitable loan structure. These models consisted of three different Bayesian Networks using different structure learning scores, namely the Bayesian Dirichlet sparse (BDs) score [26], Bayesian Information Criterion (BIC) score and K2 score [27]. The BIC score is a score that penalises complex structures while preserving important associations.

The structure for all three BNs was learnt using a score based approach, specifically the Hill-Climbing algorithm was used in conjunction with the above mentioned scores. The parameters for all three models were learnt using Bayesian Estimation with the Dirichlet prior.

The only hyperparameters used were the prior values for structure learning and parameter estimation. The BDs score was the only score that employed a hyperparameter for structure learning, specifically the equivalent sample size for the Dirichlet hyperparameters. The hyperparameters for parameter estimation consisted of the Dirichlet prior pseudo-counts.

Since the effect of the hyperparameters was not the main focus of this research, only a few values were tested using cross-validation, and the best values were selected, rather than extensively fine-tuning them. An equivalent sample size of 50 was used for BDs structure learning, and parameter estimation was performed using a Dirichlet prior with a pseudo-count of 5.

All three models were evaluated using the negative of the empirical log-loss of the full probability distribution. Among the three models, the best-performing one was chosen to generate the most suitable loan structure. Based on the negative of the empirical log-loss and computation time, the BIC model was selected.

Inference was done using Maximum A Posteriori (MAP) inference using the Variable Elimination algorithm to obtain the predicted values for the loan structure features (see list in III-B2) [27]. This approach identifies the most likely assignment for the joint distribution of the loan structure variables based on the borrower's information. This results in the most suitable loan structure for a given borrower. This MAP assignment is defined as:

$$maxP(\text{interest rate, term, instalment, loan amount} \\ \mid \text{evidence list, loan status = Fully Paid}) \quad (1)$$

To calculate the negative of the empirical log-loss to assess the most probable loan structure, the same metric will be used. However, here the joint probability being assessed will be the value of the probability (1), instead of being the full probability distribution.

All three models including the benchmark models were implemented using the PGMPY python library [28].

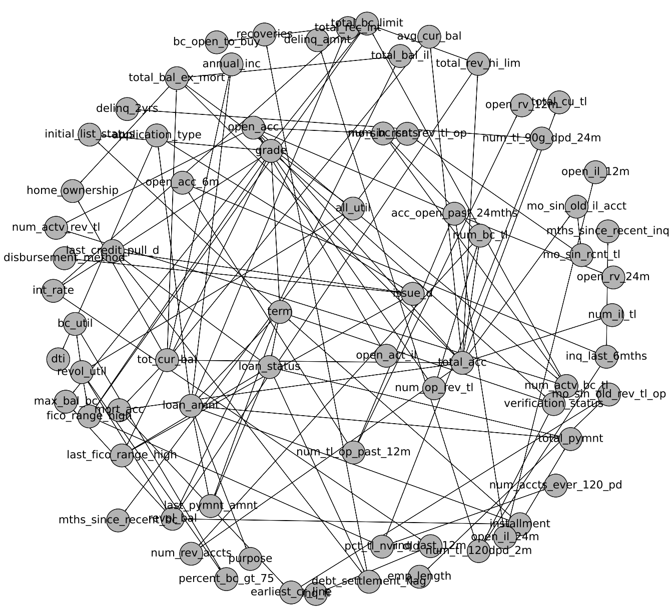

Fig. 1. Example of the BIC Structure learnt on 10k lines of Data.

E. Evaluation

The primary evaluation metric for this experiment was the negative of the empirical log-loss, also known as the Log-Likelihood score. Traditional classification metrics like F1 score and accuracy were unsuitable, as MAP inference identifies the most likely loan structure rather than matching true dataset values. Additionally, setting the loan status to "Fully Paid" causes the predicted loan structure to differ from the actual values if the borrower originally defaulted on the loan.

Both the proposed and benchmark models were evaluated using 5-fold Cross Validation, recording the log-likelihood metric for each fold and averaging the results. To assess how dataset size impacts performance, this 5-fold cross validation was repeated with dataset sizes ranging from 50 to 100,000, sampled randomly from the full dataset. These results were logged and visualised using Weights & Biases [29].

To examine the effect of borrower-specific information on loan structure predictions, the models were evaluated using varying evidence lists as defined in Section III-B2. Finally, Log-Likelihood curves for the proposed models were compared against the benchmark models.

F. Limitations of Methodology

The limitations of this methodology can be categorised into two main areas: model construction and model evaluation. Firstly, the models constructed were discrete BNs, in contrast to continuous BNs. Due to the time and space complexity of BNs, the number of discrete categories in the data had to be kept relatively low. This limitation may lead to a loss of information, reducing the precision and accuracy of the predicted loan structures, as predictions are confined to broader categories rather than specific values. A continuous BN would solve this limitation, however continuous BNs are more complex to implement and have more limited tool-kits compared to discrete BNs.

Secondly, while Log-Likelihood was used to assess the performance of loan structure predictions, it may not be the most ideal metric, as it does not provide a clear indication of the practical effectiveness or suitability of the loan structure in a real lending context. However, comparing the proposed models against the chosen benchmarks does give a good indication of the performance of the models.

G. Contributions

This research contributes by introducing an explainable ML technique to predict multiple components of a loan structure. It also contributes towards the applications of Bayesian Networks and XAI, showing they can be used more effectively in a financial setting. It advances personalisation in banking by offering a method to tailor and generate the most suitable loan for individual borrowers.

IV. Results

The figures below display the log-likelihood curves for the different experiments described in section III-D. These results are analysed in-depth to compare the proposed models with the benchmarks.

Figure 2 demonstrates that the BIC model significantly outperforms other models when working with small datasets.

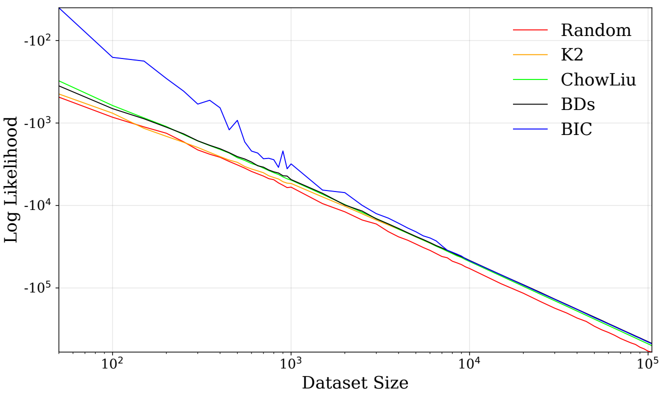

Fig. 2. Log-Likelihood Comparison of Various Models with Increasing Dataset Sizes Using 5-Fold Cross Validation

This superior performance persists until the dataset reaches approximately 8000 samples, at which point BIC's performance converges with other models, except for the Random BN. The Random BN consistently shows the poorest performance across different dataset sizes, though it occasionally outperforms the K2 BN when working with very small datasets. The plot shows a slight diverging trend where the gap between the Random BN and the other models widens as the dataset size increases. The gentler gradients of the BIC, K2, BDs, and Chow-Liu models indicate that they make better use of additional data, compared to the Random BN, whose steep gradient indicates less effective scaling.

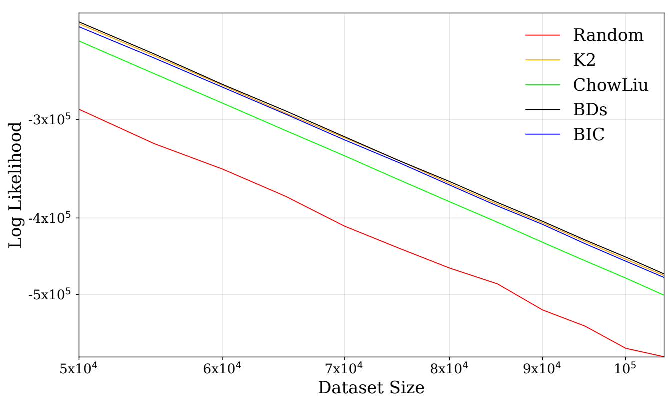

Fig. 3. Magnified Log-Likelihood Comparison of Various Models with Increasing Dataset Sizes Using 5-Fold Cross Validation

Figure 3 shows that at larger dataset sizes, the performance differences between models stabilize. In this magnified view, the three proposed models (BIC, K2, and BDs) consistently outperform both the Chow-Liu Tree and Random BN, with the performance gap being particularly pronounced against the Random BN.

Figure 4 represents the comparison of the different models' performance at predicting a suitable loan structure using the log-likelihood and MAP assignment (1) described in section III-D. This plot demonstrates that the BIC BN and the Chow-Liu Tree both perform better than the Random BN across all evidence lists, for different dataset sizes. The Chow-Liu Tree and the BIC BN perform similarly, with the Chow-Liu Tree performing slightly better when working with small datasets. However, with larger datasets the BIC performs better. Similarly to fig. 2, there is a diverging trend between the Random BN and the other models, and between the BIC BN and the Chow-Liu Tree. This indicates that the BIC model makes better use of additional data at predicting the suitable loan structure.

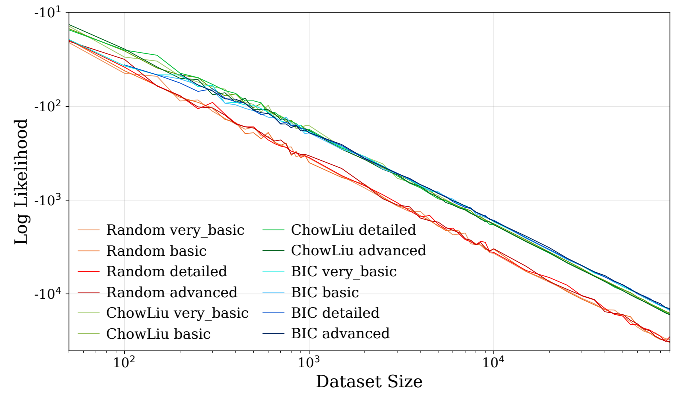

Fig. 4. Log-Likelihood Comparison of Various Evidence Lists Across Models with Increasing Dataset Sizes Using 5-Fold Cross Validation

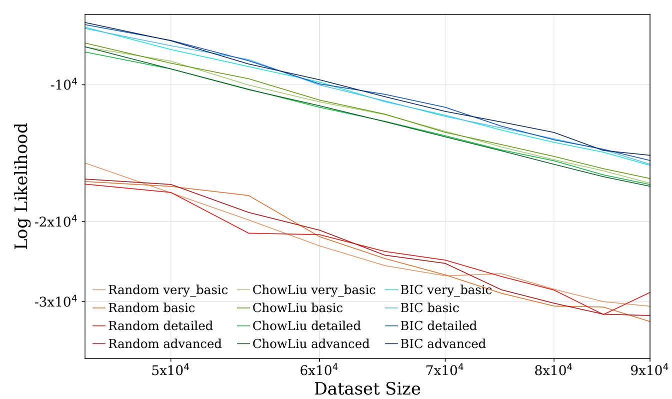

Fig. 5. Magnified Log-Likelihood Comparison of Various Evidence Lists Across Models with Increasing Dataset Sizes Using 5-Fold Cross Validation

The magnified plot, fig. 5 demonstrates the effect the amount of borrower information has on the prediction of the most suitable loan structure across the various models. The plot shows a clearer view of the superior performance of the BIC BN compared to the Chow-Liu Tree. The BIC model generally performs better if there is more borrower information available. On the other hand, increasing the amount of borrower information does not result in an increase in performance for the Chow-Liu Tree. The Random BN, does not display any trends with regards to the different evidence lists, and it is more inconsistent and displays more variance across the different evidence lists when predicting the most suitable loan structure.

It was expected that the BIC model would outperform both benchmarks, as it more accurately models the associations between the different features. However, it was not expected that the Chow-Liu would perform better than the BIC at predicting the most suitable loan structure on small datasets (4). This could be due to the fact that the BIC score constructs very sparse and small models when little data is available, therefore there may not be enough connections between relevant features in the network to accurately predict a suitable loan structure.

V. Discussion

The above results demonstrate that all three of the proposed Bayesian Networks, specifically the BIC BN, outperform the two benchmarks in fitting the loan data. This suggests that the BIC BN is a more effective method than the industry standard, especially when there is limited data available. The BIC BN also predicted more probable loan structures than the industry standards, suggesting it is able to more accurately model the loan structure holistically, given borrower information.

As seen in the above results, the dataset size and the amount of borrower information does have an effect on the model's performance when predicting a suitable loan structure for a specific borrower. This effect is particularly noticeable with the BIC Bayesian Network. This may be due to the BIC model's structure, which captures important associations between features, allowing it to effectively leverage borrower information to infer the loan structure variables. In contrast, the amount of borrower information did not affect the Random BN's performance in predicting the loan structure. This may be because the Random network consists of random associations between features, making it unable to effectively leverage the evidence to infer the loan structure variables.

The above mentioned associations also help the BIC BN to outperform the benchmarks when less borrower information is present. This is significant to the problem statement, as high-risk borrowers and SMEs that lack financial records and creditability, can still be offered a suitable loan structure that is tailored towards them.

The results are significant because the predicted loan structures were inferred using the evidence that the loan was fully paid. This fact, in conjunction with the technique of MAP inference, results in the predicted loan structures being the most suitable with the borrower having a very low possibility of defaulting on the loan.

This research provides an explainable ML approach to generate the most probable loan structure for a specific borrower. It also models multiple components of a loan structure holistically, with taking into account borrower information. It adds to the field of XAI, showing that Bayesian Networks can be applied in a financial setting to create an explainable and transparent ML framework to generate borrower-tailored loans. The explainabilty and transparency of this approach allows it to be used in financial institutions to make financial decisions. This research will benefit lenders and borrowers who face the challenges and risks involved in the lending process. Lastly, it can also be seen to build onto personalisation in banking.

There are however limitations to this research, two of which were discussed in the limitations of the methodology. The provided framework being discrete, results in lack of information and the predicted loan structures not being as fine-tuned as they can be. The predicted loan structures could also not be accurately evaluated in their real-world performance.

All code for the research can be found on Github for reproducibility purposes:
https://github.com/Zach-schwark/Honours-Research

VI. Conclusion

In conclusion, the use of explainable machine learning is suitable for generating borrower-tailored loans. This framework aims to minimise the probability of default, reducing lender risk when lending to high-risk borrowers or SMEs. By holistically modelling loan structures with borrower financial data, the approach can balance loan components, potentially lowering the need for high interest rates and reducing loan denials. Rather than simply pricing for risk, it integrates multiple aspects of the borrower's profile to create a more tailored and balanced loan structure.

The findings indicate that both dataset size and borrower-specific financial information significantly impact the Bayesian Network's ability to predict suitable loan structures. Notably, the BIC model outperforms industry standards, particularly with smaller datasets. Additionally, as dataset size and borrower information increase, the BIC model predicts more probable loan structures. In contrast, the Chow-Liu tree model benefits less from added borrower information, and the Random BN remains unaffected. Overall, the BIC model proves most effective, especially when there is limited data available.

Future work should entail looking into using continuous Bayesian Networks to achieve more accurate and fine-tuned loan structures. This work should also entail including more fine grained loan structure components, such as amortisation, collateral, and balloon payments etc. A more comprehensive method to assess the model's performance, that will give a better indication of the performance of a specific loan structure, should be taken in future research.

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ExplainableAI Lab

— MODELLING. DECISION MAKING. CAUSALITY —

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APPENDIX
DATA

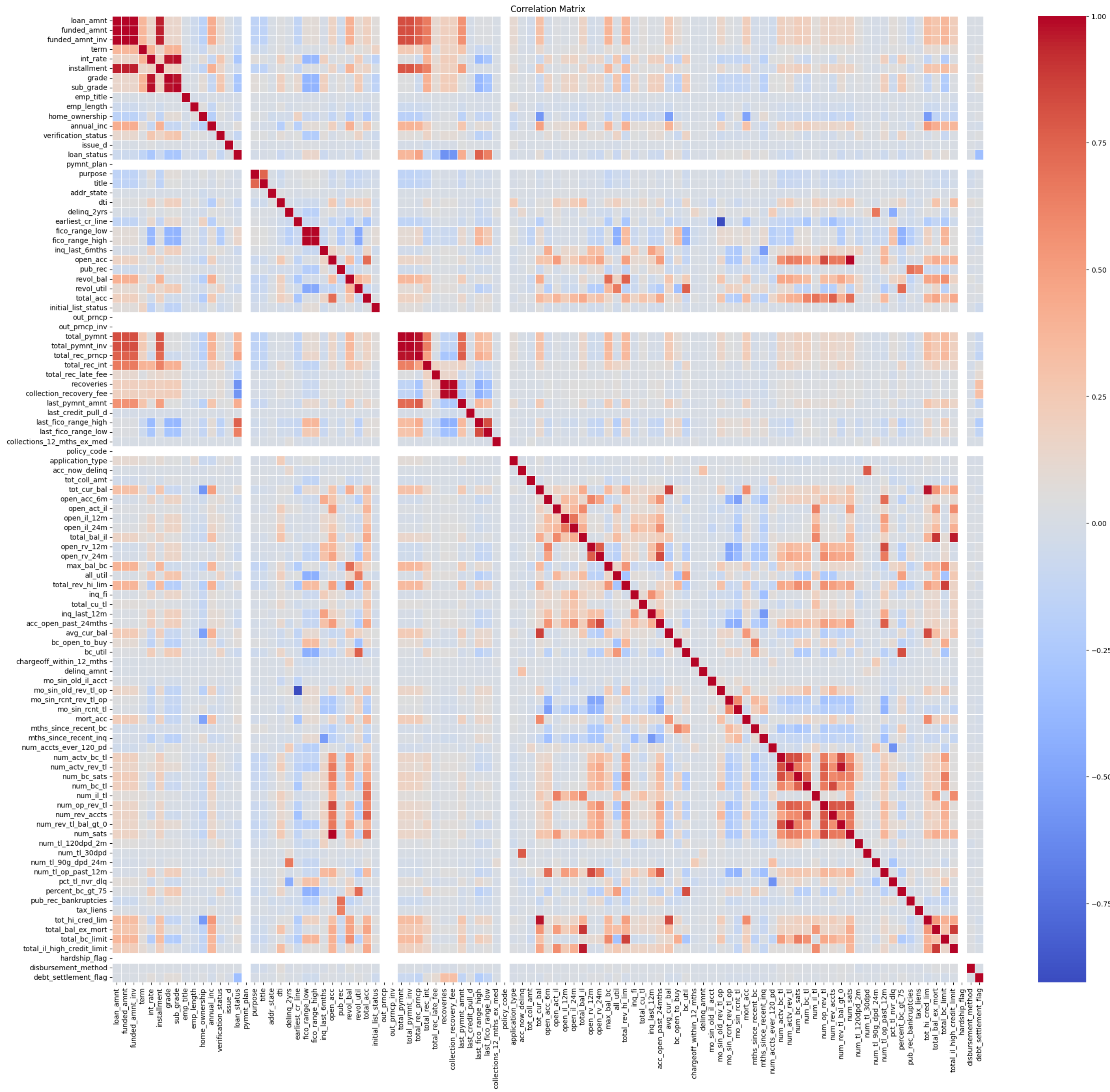

Fig. 6. Correlation Map Showing the Relationships in the data