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PolyTrunc-ANN: Polynomial Features and TruncatedSVD for Optimized Neural Network Performance for Predicting Loan Defaults in P2P Lending Platforms

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Abstract:

Peer-to-peer (P2P) lending networks have revolutionized the financial landscape by providing borrowers with alternative credit options and offering lenders new investment opportunities. Nonetheless, predicting loan defaults remains a critical challenge that demands advanced predictive models for effective risk management. This research evaluates the performance of a sophisticated predictive algorithm for loan defaults in P2P lending platforms, utilizing detailed borrower, loan, and historical default data. We identify and analyze key borrower characteristics influencing default likelihood, demonstrating that our model significantly improves prediction accuracy compared to traditional methods. Additionally, the study explores the practical implications of integrating this model into P2P platforms, including its impact on stakeholders and associated ethical considerations. The goal is to enhance the stability and reliability of P2P loan ecosystems, benefiting both investors and borrowers.

The distinctiveness of this research lies in its comprehensive approach, integrating advanced pre-processing techniques—such as parallel variable pre-processing pipelines, TruncatedSVD for dimensionality reduction, and SMOTE for class imbalance correction—with a custom-designed ANN architecture optimized through RandomizedSearchCV. Furthermore, this study employs the RandomForestClassifier to provide valuable insights into the significance of features and individual prediction explanations.

Keywords: Credit Risk Modeling, Machine Learning, Probability of Default, Borrower Creditworthiness, Default Forecasting, Credit Scoring, Peer-to-Peer Platforms.

1. **Introduction:** The power of a computer to gain insight without being explicitly programmed is known as machine learning (Samuel, 1959). Advancements in this field have greatly influenced the banking and finance sector, leading to efforts to delineate primary tasks like payment processing and risk distribution. It will also improve capital allocation as new players like payment service providers, aggregators, investors, and P2P lending platforms enter the market.

Thanks to the revolution in the FinTech space and advances in machine learning, the financial services business has been through many changes (Bachmann et al., 2011).

"FinTech" refers to services and solutions that use technology and are made possible by combined IT. FinTech payment innovations have changed how the financial industry works in the digital age. FinTech also provides banks and other financial institutions involved in lending businesses with internet platforms to help pay and transfer between networks (Shim & Shin, 2015). P2P platforms facilitate loans between individuals through digital mediums, with financial entities serving as legally mandated intermediaries. The earliest commercial online peer-to-peer lending business began in 2005 by communities in online social networks (Munusamy et al., 2013). P2P lending systems can be either commercial or non-commercial. The primary distinction between them is what the investor wants and expects regarding returns.

Investors try to invest in avenues with low risks and high returns, while borrowers with varying levels of credit risks seek avenues to access liquidity. Individuals from these diverse groups can connect through P2P apps, aiming to find mutually beneficial solutions. Those lending or borrowing money often gather in micro-communities to collaborate more effectively (Wang & Greiner, 2011; Herrero-Lopez, 2009).

By 2010, these lending platforms had become increasingly significant as confidence in online transactions grew, the desire for immediate results intensified, and the usage of analytics and publicly available data for credit scoring proliferated (Tomlinson et al., 2016). These platforms revolutionized how individuals and small to medium-sized businesses access loans. However, its volume still falls short compared to traditional lending institutions like banks. The long-term impact on the financial landscape remains uncertain. (Jagtiani & Lemieux, 2018). Governments and the regulatory authorities in the US and UK recognize the implications for their economies, leading to a significant increase in regulations between 2010 and 2015. (Ye et al., 2015). The big retail banks are either supporting these initiatives or developing comparable ideas.

Opening financial services to a larger population is appealing. P2P lenders will give consumers more power by giving them better information to help them make choices and better-targeted services; this will make things transparent and give lenders more control. As more small and medium-sized companies get credit, the range of businesses will grow. Because of this, P2P makes the sector's finances more stable (Herzenstein et al., 2008).

New models will alter systemic risks, impacting credit quality and the economy. These risks involve credit structuring, maturity changes, leveraging, and liquidity shortages. While P2P lending platforms have simple operating models, posing less systemic risk, understanding their growth and risk management is crucial (Carney, 2017). In his 2007 study, Anderson emphasized staying updated with recent advancements and leveraging available data in credit scoring, thus assisting lenders in making credit decisions.

2. Literature Review

A high default rate can damage a bank's reputation and erode investor trust, making loans to high-risk clients costly for traditional banks. Additionally, banks face extra costs from daily operations and increased capital requirements due to defaults. They also incur higher marginal costs for each additional loan than P2P lending platforms. Consequently, these reputational, capital, and operational costs incentivize banks to avoid high-risk clients and smaller loans (De Roure et al., 2016).

After studying the Zopa platform, in their 2006 study, Hulme and Wright proposed that P2P platforms could improve transparency in traditional banking. Peer-to-peer lending provides low-cost loans to borrowers and substantial returns to lenders, enhancing societal well-being. These platforms cater to niche financial transactions banks overlook, connecting borrowers who lack access to conventional credit options. For instance, aspiring entrepreneurs may not meet traditional bank criteria but can secure funding through P2P platforms. This increased loan disbursement improves overall societal well-being.

The financial crisis and subsequent unavailability of funds from traditional banking institutions contributed to the growth of P2P platforms. There is an inverse relationship between the lending volumes of mainstream financial institutions and P2P platforms—when one decreases, the other increases. This shift occurs as borrowers turn to P2P lending when traditional banks fail to meet their financial needs (De Roure, Pelizzon, Tasca, 2016). The decrease in credit availability during the financial crisis led more borrowers to seek online lending platforms, benefiting P2P lending (Havrylchyk et al., 2018). In their study, Bertsch et al. (2018) identified that the banks' misconduct led to the growth and expansion of these P2P platforms at various levels, primarily led by borrowers with low credit scores. Additionally, declining confidence in traditional banks has driven more investors to P2P platforms.

P2P lending platforms face competition from traditional financial institutions. As these institutions increase, the growth prospects for P2P platforms decrease. However, borrowers having a negative experience with traditional financial institutions turn to P2P platforms. These platforms thrive in areas with fewer conventional financial institutions, capitalizing on growth potential, especially when these institutions close physical branches (Havrylchyk et al., 2018). P2P lending involves connecting borrowers to lenders through a digital platform (Cumming & Hornuf, 2018). The small loans facilitated by P2P lending platforms led to the term 'microlending market' when the industry began (Emekter et al., 2015).

P2P lenders differ from traditional banks by not accepting deposits. They have lower entry requirements and quicker processing times, allowing borrowers to access the marketplace with less financial disclosure. Now, institutional investors invest in loan bundles through these P2P platforms, known as marketplace lending. Weiss et al. (2010) highlight the challenge of assessing borrower solvency due to digital interactions without personal identification. Traditional banks sometimes offer loans at a cheaper interest rate as they collect required data about the borrower and analyze them rigorously.

On the contrary, the P2P platform borrower screening process is less rigorous, and they offer loans primarily to those whose credit score is lower; this leads to higher interest rates on the loans they offer. P2P platforms further mitigate the default risk by offering smaller amounts of loans to the borrowers (Tomlinson et al., 2016). In their 2015 study, Emekter et al. identified the significance of FICO score, loan grade, interest rates, and debt-to-income ratio in predicting borrower default in the P2P markets. To determine the right portfolio of loans to reduce the losses and maximize the profits for the investors, the authors used the internal rate of return method as an indicator to gauge the returns (Byanjankar et al., 2021).

This study examines Lending Club, the largest P2P lending fintech till 2020, which connects lenders and borrowers for loans from USD1,000 to USD40,000. Borrowers receive the loan amount minus a processing fee, while lenders get promissory notes backed by loans and pay a service fee to the platform. These platforms make financial products more accessible and empower consumers with information and tailored services, enhancing clarity and control. Consequently, P2P lending improves the industry's financial stability.

New underwriting models in P2P lending may introduce systemic risks that affect creditworthiness and broader economic factors, particularly in credit evaluation, interest rate setting, and risk management. While small-scale P2P platforms face minimal systemic risk exposure, understanding the impact on larger platforms' growth and assessment is crucial (Carney, 2017). Credit scoring utilizes quantitative models to convert data into numeric measurements, aiding lenders in making credit decisions (Anderson, 2007). As this field evolves and develops, adapting to the latest advancements and utilizing accessible data is paramount. An effective credit rating model is crucial for peer-to-peer lending. Hence, incorporating novel types of data such as behavioral, social media, and psychological measurement data forms pivotal in enhancing the accuracy of the models (Polena, 2017).

Multiple challenges exist in P2P markets, such as fraudulent activities, economic downturn linked to the recent pandemic, and difficulty assessing borrowers' creditworthiness due to online anonymity. Thus, comprehending the dynamics of financial distress in this industry is crucial, as it did not exist during the previous global economic crisis.

3. Statement of the Problem

Although there have been improvements in data analytics, accurately forecasting credit delinquencies in P2P credit platforms continues to be a difficult task. Conventional models frequently lack precision and struggle to adequately represent the connections between borrower attributes and credit terms, leading to less-than-ideal risk control measures. Reliable and comprehensible predictive models are essential for effectively managing risk and making well-informed lending decisions. The focus of this research is to design an optimized model called PolyTrunc-ANN. This model combines polynomial characteristics, Truncated SVD, and a tailored ANN to enhance prediction accuracy and offer valuable insights into aspects contributing to default risk.

4. Need of the Study

The meteoric rise of these lending platforms has transformed the financial landscape by offering people an alternative to traditional banking systems. This growth also brings problems, especially when controlling and lowering the risk of loan defaults. Predicting the borrowers' default rates is essential for these platforms to stay stable and reliable, protect investors, and ensure fair lending. Traditional credit scoring methods have been used but don't always work well with the complicated and varied data common in peer-to-peer loans. To make default predictions more accurate, we need to look into more advanced prediction methods right away, like machine learning algorithms. This study meets this need by checking how well a machine learning algorithm predicts loan defaults, thus improving these platforms' risk management and decision-making processes.

5. Objectives of the Study

- Develop and evaluate an advanced predictive model for loan defaults in P2P platforms.
- Examine and assess the borrower attributes that influence the loan defaults in the P2P platforms.
- Enhance model robustness and generalization with the help of hyper-parameter tuning.
- Implement RandomForestClassifier for feature significance and interpretability.

6. Hypotheses of the Study

The hypotheses outlined below are proposed for evaluation.

NH-1: Implementing the EarlyStopping callback does not significantly improve the model's generalization performance, as measured by the validation loss.
NH-2: No appreciable difference is observed in the model accuracy when TruncatedSVD is applied for dimensionality reduction compared to a baseline model without TruncatedSVD.
NH-3: The inclusion of polynomial features does not significantly improve the model's performance in predicting loan defaults compared to a model without polynomial features.
NH-4: Borrower attributes (such as income, interest rate, credit history, home ownership, and loan purpose) do not exhibit any significant impact on loan defaults in P2P platforms.

7. Research Methodology

7.1 Data Source and Sample Selection

The basis for the present study on consumer lending in financial technology mainly revolves around LendingClub, which centers around crucial factors. Firstly, the business is notable for being among the few lenders who published their data for public access. Additionally, LendingClub holds the top position as a fintech supplier in the lending industry. Consequently, we anticipate that the conclusions in this context will have broader relevance. Since its inception in 2007, it has offered extensive information on every approved or rejected loan application.
We get a wide range of information about the borrowers and the loans funded; this includes specific facts about the borrowers, like their credit ratings, employment duration, debt-to-income ratio, whether they own a property, and zip code. In addition, we collect specific information about the loan, such as the interest rates, the time until it is due, the initiation date, the intended use of the loan, and the verification status. In addition, we monitor the monthly repayment and performance of each loan.

Data forms a crucial prerequisite for high-quality studies. In this research, the dataset from LendingClub's official website includes 466,280 observations spanning 2007 to 2015. Certain features like borrower zip codes, membership IDs, and attributes having substantial missing values are dropped from the analysis. The study concentrates on loan status, loan purposes, borrowed amounts, and borrower creditworthiness as critical components.

7.2 Tools Utilized

The dataset comprises a mix of quantitative and qualitative variables. The study uses Anaconda Navigator, a desktop graphical user interface included in the Anaconda distribution, and the programming language Python and its libraries numpy, pandas for data analysis, model building using machine learning algorithms, and matplotlib for data visualization within interactive development environments. The study used descriptive statistics and visual tools to review the data. Graphs like column charts, box plots, and histograms help us see how the data got distributed. The pd.read_csv method in pandas takes data from data frames; this makes it ideal for managing data so that it can be changed and analyzed in different ways.

7.3 Data Pre-processing Techniques

During the initial pre-processing phase, we use the pandas library to load the dataset and then utilize the `data.info` method to gather fundamental details, including the count of missing values and data types for each attribute. The dependent variable is transformed into a binary representation of 0 (defaulters) and 1 (non-defaulters). The categorical variables are processed using the SimpleImputer class within the sklearn.impute module for imputing the missing values, scaling, and then transforming the variables into dummy variables using OneHotEncoder, followed by designing a pipeline to handle the pre-processing of the numerical variables in terms of standardizing using the StandardScaler class and imputing the missing values and a subsequent application of ColumnTransformer class for employing the pre-processing techniques on categorical and numerical variables in parallel. The TruncatedSVD method aptly handles the curse of dimensionality by reducing the high-dimensional space into a low-dimensional subspace, thus decreasing the complexity within the variables and accelerating the model training. SMOTE handles the class imbalance within the training data. After pre-processing, the data is split, allocating 70% for training and 30% for testing. A significant portion of the data was allocated to training to ensure the variance in the data was captured, keeping ample data for testing.

7.4 Model Building and Hyperparameter Tuning

A high-level application programming interface, Keras framework for TensorFlow, was employed to train the artificial neural networks (ANN). This ANN architecture comprises an input, dense, and output layer. The input layer is built to handle the data that matches the number of independent features from the pre-processed dataset. In the first hidden layer, 32 neurons are paired with the Rectified Linear Unit (ReLU) activation function to handle the dataset's complex patterns, followed by adding a drop-out layer to prevent overfitting. Next, we add the second hidden layer comprising 16 neurons, an activation function, and a drop-out layer. A single neuron with a sigmoid activation function is used in the output layer to predict binary values.

The compilation phase consists of the binary cross-entropy loss function to measure the model's performance in predicting the positive class and the Adam optimizer for updating the weights. The KerasClassifier wraps the model from the Scikeras library to integrate Scikit-learn's evaluation tools with the Keras model. To optimize the ANN model's performance, hyperparameter-tuning of epochs, batch size, and drop-out rate was done using RandomizedSearchCV. RandomizedSearchCV employs a randomized search to identify the best hyperparameter combination that provides the best model performance. Parallel processing is used alongside 3-fold cross-validation to determine the optimal hyperparameter combination. Detailed logs during the training process were provided by enabling the verbose option. Early stopping was added to the model building to avoid over-fitting by halting the training process when no improvement is witnessed in the validation loss.

7.5 Model Evaluation

The best_model is arrived at by re-training the model with the help of the best optimal parameters identified through hyper-parameter tuning. A confusion matrix and accuracy, precision, recall, and F1-score metrics are used to assess the model's performance. The training and validation loss values over epochs are visualized to understand the model's learning progress and detect the signs of overfitting and underfitting problems.

8. Findings

The training completed 50 epochs with 1238 batches per epoch. Training loss was 0.2544 and validation loss 0.2578, with each epoch lasting about two seconds. These losses gauge how well the model learns and performs on new data. Graphical analysis helps assess the model's learning trends. Ideally, both losses should decrease consistently. A higher validation loss suggests potential overfitting, impacting model accuracy.

Epoch	Batch	Average Time (ms per batch)	Training Loss	Validation Loss
1	10599	45s	0.6097	0.5762
5	10599	26s	0.4472	0.3937
15	10599	25s	0.3284	0.2814
25	10599	32s	0.2984	0.2556
35	10599	26s	0.2782	0.2495
45	10599	26s	0.2688	0.2365
46	10599	25s	0.2699	0.2348
47	10599	26s	0.2681	0.2408
48	10599	26s	0.2679	0.2403
49	10599	25s	0.2672	0.2372
50	10599	24s	0.2671	0.2360

Table 1: Summary - Epoch Training and Validation Losses Before Implementing EarlyStopping Callback

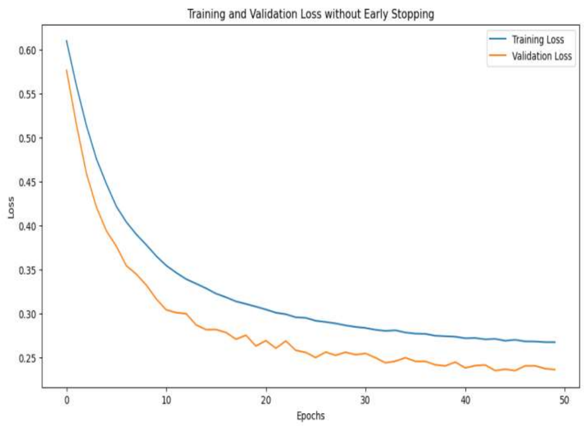

Figure 1: Changes in Training and Validation Losses

The graph shows higher validation loss than training loss, prompting parameter adjustments. The classification table lists the f1-score, specificity, and sensitivity for category 0 (non-defaulting) and 1 (defaulting) borrowers. Accuracy is approximately eighty-seven percent.

	0	1	Accuracy	
Specificity	0.98	0.85	0.90	
Sensitivity	0.83	0.98	0.90	
F1-score	0.90	0.91	0.90	

Table 2: Analysis of the Neural Network

Model's Performance

To resolve the validation loss exceeding training loss and improve the model's accuracy, we implemented the 'EarlyStopping' callback method during the training.

Epoch	Batch	Average Time (ms per batch)	Training Loss	Validation Loss
1	10599	59s	0.6117	0.5797
5	10599	28s	0.4435	0.3928
10	10599	25s	0.3613	0.3147
15	10599	25s	0.3283	0.2878
20	10599	25s	0.3103	0.2711
25	10599	24s	0.2975	0.2636
26	10599	24s	0.2852	0.2570
27	10599	23s	0.2733	0.2530
28	10599	23s	0.2724	0.2402
29	10599	23s	0.2685	0.2408

Table 3: Summary - Epoch Training and Validation Losses After Implementing EarlyStopping Callback

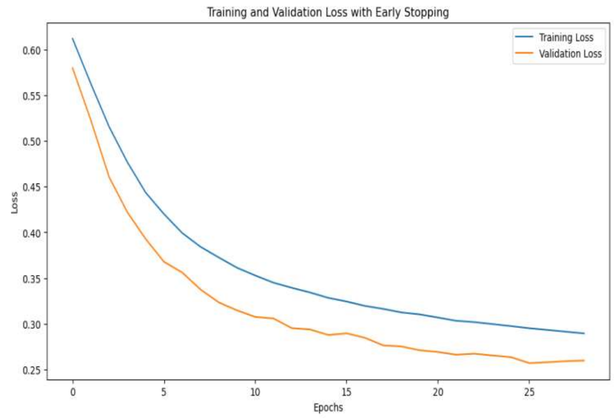

Figure 2: Loss Curves Over Epochs After Applying Early Stopping Callback

The 'Early Stopping Callback' method tracks the losses with a patience threshold of five epochs. If validation loss fails to decline, the training process stops with immediate effect. This technique reduces overfitting and improves the model's generalization. The graph illustrates that validation loss decreases compared to training loss, signifying better learning. The classification table also reflects higher accuracy.

	0	1	Accuracy
Specificity	0.97	0.84	0.88
Sensitivity	0.81	0.96	0.88
F1-score	0.89	0.90	0.88

Table 4: Model Performance After Applying Early Stopping

The dataset is characterized by significantly more fully paid loans than charged-off loans. The specificity, sensitivity, and f-score are the key parameters to monitor. The model attained a specificity level of approximately eighty-nine percent. The accuracy rate of the forecasting algorithm for predicting when debt is charged-off is forty-five percent.

Referring to the results outlined in **Table 1 and Table 2,** the validation loss with EarlyStopping is slightly higher (0.2408) than without EarlyStopping (0.2360). However, we reject the null hypothesis **(NH-1)**, considering that EarlyStopping achieved this earlier (by Epoch 29) and avoided the additional epochs that might lead to overfitting. The EarlyStopping callback helps improve the model's generalization by stopping the training before overfitting can occur, making the training process more efficient while maintaining a comparable validation loss.

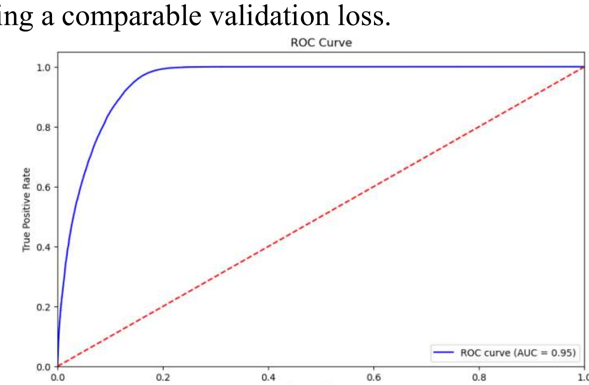

Figure 3: AUC-ROC curve for without TruncatedSVD Model

Given that the model without TruncatedSVD consistently outperforms the model with TruncatedSVD across all metrics such as accuracy, ROC-AUC (0.95), KS Statistic (0.8092), and Gini coefficient

(0.9061). The data in **Table-5** shows a significant decrease in validation accuracy (0.8592) and an increase in validation loss (0.3240) when TruncatedSVD is applied. Therefore, we reject the null hypothesis **(NH-2)**. The baseline model without TruncatedSVD performs better than the model using these techniques.

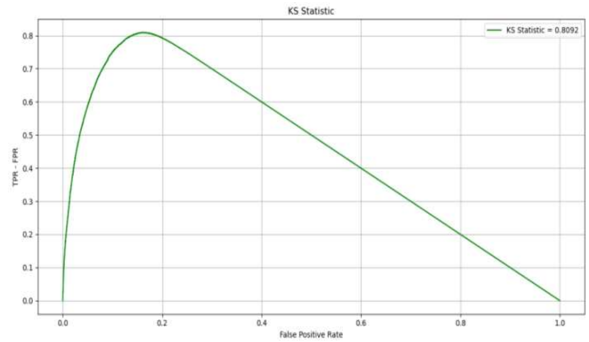

Figure 4: K-S Statistic curve for without TruncatedSVD Model

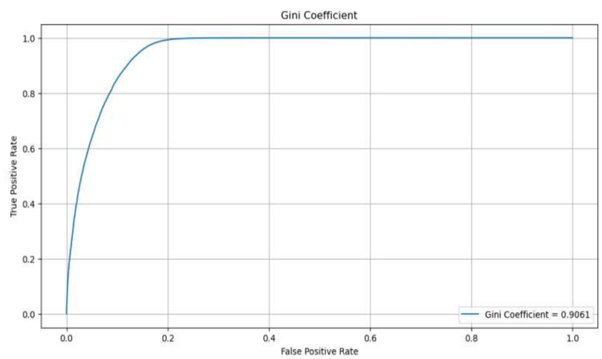

Figure 5: Gini Coefficient curve for without TruncatedSVD Model

Given that the model without TruncatedSVD and with Polynomial Features consistently outperforms the model without TruncatedSVD and without Polynomial Features across all metrics such as accuracy (0.9052), ROC-AUC (0.95), KS Statistic (0.8092), and Gini coefficient (0.9061). The data in **Table-5** shows a significant decrease in validation accuracy (0.8525) and an increase in validation loss (0.3253) when model is built without TruncatedSVD and without Polynomial Features. Therefore, we reject the null hypothesis **(NH-3)**. The baseline model without TruncatedSVD and with Polynomial Features performs better than the other models.

Given that the important attributes plot in **Figure-6** shows that several borrower attributes (such as loan purpose, home ownership, verification status, and interest rate) have significant importance in predicting loan defaults, we reject the null hypothesis **(NH-4)**. These attributes exhibit a significant impact on loan defaults in P2P platforms.

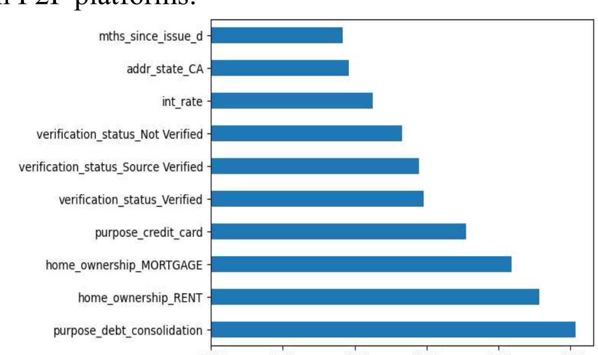

Figure 6: Important Attributes

9. Suggestions

It is recommended that the dataset be beefed up by including a wide range of sources to strengthen the model's potential to apply to a broader range of situations. Improve the feature engineering process by incorporating interaction terms to more accurately capture the behavior of borrowers and the features of loans. To evaluate its relative effectiveness, compare the PolyTrunc-ANN approach with other sophisticated algorithms, like ensemble approaches. Integrate temporal data to consider historical patterns and variations in borrower conduct. Perform a comprehensive impact assessment to assess the influence of the model on stakeholders, such as lenders and borrowers. Examine ethical factors to prevent prejudices and promote fairness. Test the model in an actual environment to confirm its efficacy. Enhance the interpretability of the model by integrating supplementary explanation techniques to gain more profound insights into forecasts.

10. Conclusion

Automating the process of predicting the loan default models has wider ramifications; they help the investors, and the P2P platforms assess the borrowers' creditworthiness, curtailing the default risk and increasing the investors' trust in these P2P platforms. This paper discusses artificial neural network (ANN) techniques to analyze the borrowers' credit default by using the P2P lending dataset. Financial organizations lending money are crucial in enhancing individuals' overall quality of life. Furthermore, financial institutions' condition significantly impacts the overall functioning of a country's finances. Social loans have been gaining considerable significance as an alternate fundraising method. A crucial aspect for financial institutions involved in lending is implementing rigorous credit risk management to minimize its impact on the institution's economic health.

Currently, where data analysis using advanced pre-processing techniques is becoming increasingly important, firms have access to several approaches to enhance the administration of different processes. Various econometric models are employed to assess and control credit risk accurately. Several studies examine the efficacy of various methods in accurately categorizing customers as good (those who make loan repayments on time) or bad (those who do not make loan repayments on time). The selection of an optimal classifier is crucial in managing the percentage of non-performing loans within a financial institution's portfolio, thereby impacting its operational efficiency.

11. Limitations

Tweaking some of the parameters of our model would lead to improved outcomes. One such approach is to conduct experiments by varying the number of hidden neurons and layers. Furthermore, we should contemplate incorporating simplified feature engineering techniques that may overlook complex patterns. Ignoring class imbalance between the two categories of default and non-default may skew accuracy, necessitating thorough consideration of fi-score, specificity, and sensitivity. Cross-validation approaches can enhance models' robustness and applicability across diverse datasets. In light of the time and effort needed, future academic endeavors can utilize it.

12. Future Work

We recommend implementing sophisticated feature engineering methods to capture intricate relationships within the data. Employ more advanced imputation techniques to address missing variables and mitigate bias. Resolve the issue of imbalanced class distribution by employing methods such as SMOTE. Explore the use of ensemble methods to improve forecast accuracy. Conduct thorough hyper-parameter optimization and cross-validation to enhance and evaluate the model's resilience. Integrate temporal analysis to improve comprehension of patterns related to time. Evaluate the model using external datasets to assess its ability to apply to different scenarios.

13. References

1. SHIM, Y.; SHIN, D. H. 2016. Analyzing China's Fintech Industry from the Perspective of Actor-Network Theory. *Telecommunications Policy,* vol. 40, no. 2, 168–181.
2. Wang, H., & Greiner, M. E. (n.d.). Prosper—The eBay for Money in Lending 2.0. AIS Electronic Library (AISeL). https://aisel.aisnet.org/cais/vol29/iss1/13/
3. Bachmann, Becker, Buerckner, Hilker, & Funk. (2011, August). *Online Peer-to-Peer Lending – A Literature Review*. https://www.arraydev.com/commerce/jibc/. Retrieved May 18, 2024, from https://www.researchgate.net/profile/Burkhardt-Funk/publication/ 236735575_ Online_Peer-to-Peer_Lending--A_Literature/links/54d9fb820cf24647581ff432/ Online-Peer-to-Peer-Lending--A-Literature.pdf
4. Herrero-Lopez, SNA-KDD '09: Proceedings of the 3rd Workshop on Social Network Mining and Analysis, June 2009, Article No.: 3, Pages 1 – 8, https://doi.org/10.1145/1731011.1731014
5. Jayaram, E. S., Balachandar, G., & Kumar, K. (2024). Machine Learning-Based Loan Default Prediction: Models, Insights, and Performance Evaluation in Peer-To-Peer Lending Platforms. Educational Administration: Theory and Practice, 30(5), 12975-12989.
6. Ye, X., Dong, L. A., & Ma, D. (2018). Loan evaluation in P2P lending based on a random forest optimized by a genetic algorithm with a profit score. Electronic Commerce Research and Applications, 32, 23–36. https://doi.org/10.1016/j.elerap.2018.10.004
7. Polyzos, S., Samitas, A., & Rubbaniy, G. (2023, May 29). *The perfect bail-in: Financing without banks using peer-to-peer lending*. International Journal of Finance & Economics/ International Journal of Finance and Economics. https://doi.org/10.1002/ijfe.2838
8. de Roure, Calebe and Pelizzon, Loriana and Tasca, Paolo, How Does P2P Lending Fit into the Consumer Credit Market? (2016). Bundesbank Discussion Paper No. 30/2016, Available at SSRN: https://ssrn.com/abstract=2848043 or http://dx.doi.org/10.2139/ssrn.2848043
9. Hulme, K., & Wright. (2006). Internet Based Social Lending: Past, Present and Future. Social Futures Observatory.
10. Havrylchyk, Olena, Mariotto, Carlotta, Rahim, Talal and Verdier, Marianne. "The Expansion of Peer-to-Peer Lending" Review of Network Economics, vol. 19, no. 3, 2020, pp. 145-187. https://doi.org/10.1515/rne-2020-0033
11. Cumming, D. J., & Hornuf, L. (2020). Marketplace lending of SMEs.
12. Emekter, R., Tu, Y., Jirasakuldech, B., & Lu, M. (2015). Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending. Applied Economics, 47(1), 54-70. https://doi.org/10.1080/00036846.2014.962222
13. Weiss, G. N., Pelger, K., & Horsch, A. (2010). Mitigating adverse selection in p2p lending–Empirical evidence from prosper. com. Available at SSRN 1650774.
14. Christoph Bertsch, Isaiah Hull, Yingjie Qi, Xin Zhang, Bank misconduct and online lending, Journal of Banking & Finance, Volume 116, 2020, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2020.105822
15. Serrano-Cinca, C., Gutiérrez-Nieto, B., & López-Palacios, L. (2015). Determinants of default in P2P lending. *PloS one*, *10*(10), e0139427.
16. Zhang, Bryan Zheng and Baeck, Peter and Ziegler, Tania and Bone, Jonathan and Garvey, Kieran, Pushing Boundaries: The 2015 UK Alternative Finance Industry Report (February 3, 2016). Available at SSRN: https://ssrn.com/abstract=3621312 or http://dx.doi.org/10.2139/ssrn.3621312

17. Abdou, H. A., &Pointon, J. (2011, April 1). *Credit Scoring, Statistical Techniques, and Evaluation Criteria: A Review of the Literature*. Intelligent Systems in Accounting, Finance, and Management. https://doi.org/10.1002/isaf.325
18. Mammadova, Leyla (2021). Peer-to-peer (P2P) lending: default, default dependency, and industry potential. Loughborough University. Thesis. https://doi.org/10.26174/thesis.lboro.14544420.v1
19. Lahsasna, Ainon, R., &Wah, T. (2008, September 25). *Credit Scoring Models Using Soft Computing Methods: A Survey*. https://www.ccis2k.org/.
20. Wu, T. P., Wu, H. C., Chen, B., Lin, Q., & Zou, T. (2019, October 1). *Does P2P Lending Affect Bank Lending? Evidence from China. | Journal of Applied Economics & Business Research | EBSCOhost*. https://openurl.ebsco.com/EPDB%3Agcd%3A1%3A10212561/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A140997784&crl=c
21. Lessmann, S., Baesens, B., Seow, H., & Thomas, L. C. (2015, November 1). *Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research*. European Journal of Operational Research. https://doi.org/10.1016/j.ejor.2015.05.030
22. Serrano-Cinca C, Gutiérrez-Nieto B, López-Palacios L (2015) Determinants of Default in P2P Lending. PLoS ONE 10(10): e0139427. https://doi.org/10.1371/journal.pone.0139427
23. Jiang, C., Wang, Z., Wang, R. et al. Loan default prediction by combining soft information extracted from descriptive text in online peer-to-peer lending. Ann Oper Res 266, 511–529 (2018). https://doi.org/10.1007/s10479-017-2668-z
24. Aliano M., Alnabulsi K., Cestari G., Ragni S. (2023). Peer-to-Peer (P2P) Lending in Europe: Evaluating the Default Risk of Borrowers in the Context of Gender and Education. European Scientific Journal, ESJ, 19 (7), 60. https://doi.org/10.19044/esj.2023.v19n7p60
25. Polyzos, S., Samitas, A., &Rubbaniy, G. (2023, May 29). The perfect bail-in: Financing without banks using peer-to-peer lending. International Journal of Finance & Economics/ International Journal of Finance and Economics. https://doi.org/10.1002/ijfe.2838

Best Parameter Table

	Without TrucatedSVD and with Polynomial Features		**With TrucatedSVD and with Polynomial Features**		**Without TruncatedSVD and Without Polynomial Features**	
Accuracy	Before Implementing EarlyStopping Callback	After Implementing EarlyStopping Callback	Before Implementing EarlyStopping Callback	After Implementing EarlyStopping Callback	Before Implementing EarlyStopping Callback	After Implementing EarlyStopping Callback
Training Accuracy	0.8920	0.8816	0.8502	0.8421	0.8529	0.8386
Validation Accuracy	0.9027	0.8982	0.8698	0.8592	0.8608	0.8525
Testing Accuracy	0.9044	0.9052	0.8611	0.8570	0.8631	0.8515
Training Loss	0.2671	0.2685	0.3359	0.3507	0.3269	0.3475
Validation Loss	0.2360	0.2408	03060	0.3240	03012	0.3253
Best Parameters						

Model_optimizer	Adam	Adam	Adam	Adam	Adam	Adam
Model_dropout_rate	0.2	0.2	0.2	0.2	0.2	0.2
Number of Epochs	50	50	50	50	50	50
Stopped	50	29	50	29	50	15
Batch_size	40	20	40	20	40	20

Table 5: Comparison of Neural Network Performance with and without TruncatedSVD and Polynomial Features before and after Applying EarlyStopping Callback

Summary Table

Epoch	Batch	Average Time (ms per batch)	Training Loss	Validation Loss
1	10599	25s	0.5827	0.4830
5	10599	22s	0.3770	0.3469
10	10599	22s	0.3543	0.3286
11	10599	22s	0.3524	0.3295
12	10599	22s	0.3512	0.3240
13	10599	21s	0.3508	0.3293
14	10599	21s	0.3488	0.3260
15	10599	21s	0.3475	0.3253

Table 6: Epoch Training and Validation Losses without TruncatedSVD and without Polynomial Features

Confusion Matrix Table

	Without TrucatedSVD and with Polynomial Features			**With TrucatedSVD and with Polynomial Features**			**Without TruncatedSVD and Without Polynomial Features**		
	Predicted			**Predicted**			**Predicted**		
Actual		Bad (0)	Good (1)		Bad (0)	Good (1)		Bad (0)	Good (1)
	Bad (0)	54937	11515	Bad (0)	51844	14608	Bad (0)	50646	15806
	Good (1)	1286	64748	Good (1)	3797	62237	Good (1)	3862	62172

Table 7: Confusion Matrices for Loan Default Prediction Models with and without TruncatedSVD and Polynomial Features