LAPS: Computing Loan Default Risk from User Activity, Profile, and Recommendations

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***Abstract*—The credit score is one variable in receiving a loan application from a bank or financial institution that provides credit/loan. Many factors determine whether a borrower gets the loan. One of them is through more valuable collateral than the loan that was proposed. However, this is not possible for borrowers to provide it. Personal data, job information, salary amounts, assets owned, and valuable documents are usually required to determine a credit score. We build a personal lending platform model based on the trustworthiness score called LAPS (Loan Risk score, Activity score, Profile score, and Social Recommendation score) borrower trustworthiness score. The borrowers' trustworthiness is an absolute requirement to ensure they can repay the loans and installments on time. We present the practical ways to select the best features from the Bank Marketing dataset. The feature selection of the dataset applies to blockchain applications. The advantage of LAPS is introducing recommenders' as guarantors to convince the lenders'/investors' and minimizes collateral by implementing a LAPS.**

***Index Terms*—Activity, Blockchain, Collateral, Dataset, Features, Lending Platform, Profile, Loan Risk, Recommendation, Trustworthiness.**

I. Introduction

Credit scoring issues will help the bank or financial institution get valid information, and several features describe the eligible borrowers [1]. A personal loan is part of financial services for who person applying for some loan. Traditional mechanisms show weaknesses because it takes time uncertain (it tends to be longer), require many documents, additional costs, etc. Finally, there is no transparency when the borrower is approved or rejected. In the traditional lending application process, persons apply for a loan because they need some funds to support family members, rent a house, buy a car, etc. So they try to find a loan shown in Fig. 1. Many borrowers have been rejected because they do not meet terms and conditions [2].

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Today, banks and financial institutions provide loans with terms and conditions that are not easy for borrowers to fulfill these conditions [3]. Banks or Lending marketplaces offer loans and still require collateral to guarantee that borrowers return their loans. Collateral can be in the form of assets that are easier to become money. A guarantor is a person who gives some guarantees to borrowers while applying for some loans.

Type of debt financing and approval percentages are shown in Table I below. Borrowers approval rates are shown in Cash

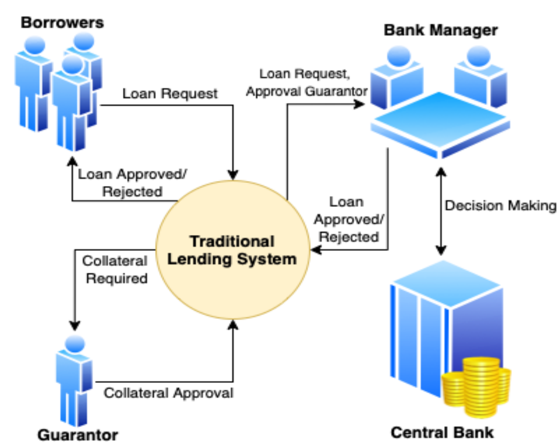


Fig. 1. A Traditional lending system

Advance Lenders 90% is higher because of fast processing about 1-3 days approval, next followed by Alternative Lenders reach 70% loan processing environs 5-7 days, Traditional Banks about 45%, about 25% time processing about 14-30 days is the last less percentage is Large Banks. Table I shows the scale of ratio and time processing impacts borrowers' proposal of some loans [4]. Table I describes it is still difficult to obtain some loans from traditional lending systems. The percentage approval was assumed from 100 borrowers. Of the Large Banks, 25 were approved, and 75 are denied in proposed loans. We provide the LAPS formula as a solution to the problem above. It contains the Loan Risk, Activity, Profile, and Social Recommendation score as a borrower trustworthiness score. The borrower has confidence after receiving the trustworthiness score. With this score, the borrower does not need any more collateral. From the lender/investor side, they get assurance that the borrower can repay the loan, and the recommender bridges the gap between the borrower and the lender. With LAPS, all users will get incentives that can be applied safely. In addition, we present the advantages of LAPS when it applies to the Ethereum blockchain-based application [5], which illustrates how to feature selection from UCI Bank Marketing public dataset [6]. This paper's remainder is structured as follows: Section I introduces the traditional lending system, stakeholders, and background literature. Section II related work. Section III is our proposal. Section IV result and discussion. Section V concludes this paper.

TABLE I: Approval Rates

Type of Debt	Percentage (%)
Traditional Banks	45
Cash Advance Lenders	90
Alternative Lenders	70
Large Banks	25

Source:https://gudcapital.com/types-of-business-loans/

II. Related Work

We found that most of the existing solutions reviewed still can be improved by detailing this research. This section's work review is found in the literature-related documents. The research mentioned how the BLockchain-Enabled Social credits System (BLESS) applied in the system leverages the decentralized architecture of the blockchain network, which allows grassroots individuals to participate in the rating process of a social credit system (SCS) and provides tamper-proof of transaction data in the trustless network environment. The anonymity in blockchain records also protects individuals from being targeted in the fight against powerful enterprises. A smart contract-enabled authentication and authorization strategy prevent unauthorized entities from accessing the credit system. The BLESS scheme offers a secure, transparent, and decentralized SCS. However, they have difficulty implementing technology in social aspects such as public acceptance and mass adoption [2].

Their research is developing a credit-scoring model using logistic regression and multivariate discriminant analysis applied in Morrocan Financial Institutions (MFIs). The model combines behavioral and descriptive data related to the borrowers (age, activity, level of education, number of unpaid debts, number of loans, etc.) and (amount of credit, duration of credit, number of concluded loans per portfolio manager, etc.). The weaknesses are required a more extensive data sample, a deep enough history of the behavior of the customer, and also more information about variables related to the client's activity and its performance to predict the default better [7].

III. Our Proposal

Features selection is needed to choose high-quality data. The selection process requires a parameter or expected value corresponding to data availability. In particular, personal data, educational background, marital status, family members, financial data, job information, and collateral. The comparative study of several methods like Decision tree [8], statistical and Artificial Intelligent [9], Rough and Tabu search [10] are relevant with research area some author had to deliver the message bring some information for selection feature, and describe the result. Features collection of datasets is tested to indicate suitability for applying the formula/model. Datasets are used from UCI machine learning is a public dataset [6].

A. Dataset Features Selection

Data sources in Fig. 2 are built with some components to be analyzed, features, and fields with a particular purpose. The phase of analysis in Fig. 3 is identifying what needs and being understood, features are about what kind of information needs and more specific, and fields describing an object are analyzed (applicant) [6]. Datasets contain the features collections and row data in Fig. 3, which should be analyzed like the data required approaches in this case. We use the association rules and the weighting approach to select the suitable features for this research. Some features are selected to represent the variable candidate with the high impact factor. The features selection is essential for choosing the best variable to support personal lending [11]. The process will start with feature collection from datasets see in Fig. 3, then continue with features selection by applying a suitable method and testing all the features selected, and the same cycle for the following features until found the highest score of features. In this section, the feature prediction phase predicts the appropriate features for the meaning of borrowers' candidates. Then, in the features selection methodology, apply some methods to get the best feature corresponding to the borrowers' profile. After the features selection has finished, we must test all features sample to ensure it is suitable for our research. Finally, we have the best features selection, supporting the credit scoring for selecting the best applicant with the minimum risk.

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	poutcome	emp.
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	may	fri	...	2	999	0	nonexistent	
1	39	services	single	high.school	no	no	no	telephone	may	fri	...	4	999	0	nonexistent	
2	25	services	married	high.school	no	yes	no	telephone	jun	wed	...	1	999	0	nonexistent	
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	fri	...	3	999	0	nonexistent	
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	mon	...	1	999	0	nonexistent	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
4114	30	admin.	married	basic.6y	no	yes	yes	cellular	jul	thu	...	1	999	0	nonexistent	
4115	39	admin.	married	high.school	no	yes	no	telephone	jul	fri	...	1	999	0	nonexistent	
4116	27	student	single	high.school	no	no	no	cellular	may	mon	...	2	999	1	failure	
4117	58	admin.	married	high.school	no	no	no	cellular	aug	fri	...	1	999	0	nonexistent	
4118	34	management	single	high.school	no	yes	no	cellular	nov	wed	...	1	999	0	nonexistent	

4119 rows × 21 columns

Fig. 2. Bank Marketing dataset

B. LAPS Splitting Formula

We briefly discuss membership functions variables rules for making a decision and define the trustworthiness score in terms of four variables [5], namely *LAPS (Loan Risk,*

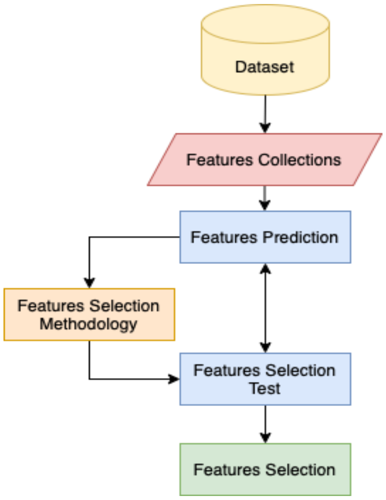


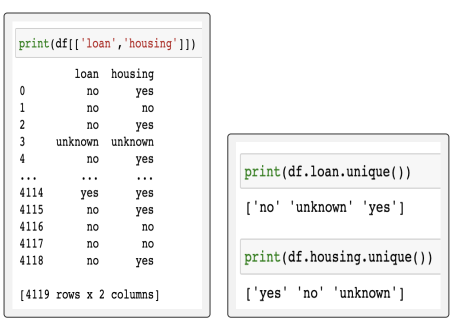
Fig. 3. Model process of Features Selection

Activity, Profile, and Social Recommendation) as borrower trustworthiness score [12], see Equation 4. The authors applied the Bank Marketing dataset from UCI public dataset [6] show in Fig. 2:

1) *Loan Risk score* is the component for measure the borrower candidate has the other loan such as housing, car, etc. in Fig. 4 (a), (b), if there is any another loan is risky to allowing get another loan and will decreasing the trustworthiness score, see Equation 1.

$$Loan\ Risk\ score = \sum_{i=1}^{n}(w_i * L_i) \tag{1}$$

where:
w = Weight for each variable $\{w\ in\ \mathbb{R} \mid w \leq 1\}$, that able to be defined by user.
i = Sequence of weight and variable.
L = Variables (loan, housing), where $\{L\ in\ \mathbb{Z} \mid L \leq 100\}$, and scale of values are between 0 to 100.



(a) (b)

Fig. 4. Loan and Housing Dataset (a) and List of Loan and Housing (b)

2) *Activity score* describing the borrower activity in occupation such as job or business activity in Fig. 5 (a), (b), to measure the ability to pay and considering the credit plafond or credit limit that correspond with their activity, if borrower candidate has a good occupation they will get the highest value of *Activity score*, see Equation 2.

$$Activity\ score = \sum(A) \tag{2}$$

where:
A = Variable (Job activity), where $\{A\ in\ \mathbb{Z} \mid A \leq 100\}$, and scale of values are between 0 to 100.

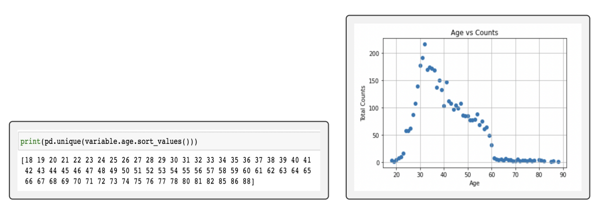
(a) (b)

Fig. 5. Job Dataset (a) and List of Job (b)

3) *Profile score* is the personal data of borrower candidates such as age, education level, and marital status in Fig. 8. These variables support to trustworthiness score. For example, the borrower should be older than 18 years old and 88 years old maximum age show in Fig. 6 (a), (b), [13], have an education level in Fig. 7 (a) to measure the economy and activity in industry or entrepreneur, and have marital in Fig. 7 (b) status to consider the family dependent. All the variables summarise in one variable as *Profile score*. The formula to get the *Profile score* is shown in Equation 3:

$$Profile\ score = \sum_{i=1}^{n}(w_i * P_i) \tag{3}$$

where:
w = Weight for each variable $\{w\ in\ \mathbb{R} \mid w \leq 1\}$, that able to be defined by user.
i = Sequence of weight and variable.
P = Variables (age, education, marital) are $\{P\ in\ \mathbb{Z} \mid P \leq 100\}$, where scale of values is between 0 to 100.



(a) (b)

Fig. 6. Range of Age (a) and Diffusion of Age (b)

```
print(df.education.unique())

['basic.9y' 'high.school' 'university.degree' 'professional.course'
 'basic.6y' 'basic.4y' 'unknown' 'illiterate']
```

(a)

```
print(df.marital.unique())

['married' 'single' 'divorced' 'unknown']
```

(b)

Fig. 7. List of Education level (a) and List of Marital Status (b)

```
print(df[['age','education','marital']])

      age          education  marital
0      30           basic.9y  married
1      39        high.school   single
2      25        high.school  married
3      38           basic.9y  married
4      47  university.degree  married
...   ...                ...      ...
4114   30           basic.6y  married
4115   39        high.school  married
4116   27        high.school   single
4117   58        high.school  married
4118   34        high.school   single

[4119 rows x 3 columns]
```

Fig. 8. A Profile Dataset

4) *The social recommendation score* is the primary variable the borrower gets support directly from the other users to add recommendation value. This values to as a guarantor for borrowers to get some loan from lenders/investors through the lending platform see in Equation 4, 5. *Social Recommendation score* = variables S (Social Recommendation) are $\{S \textit{ in } \mathbb{Z} \mid S \leq 100\}$, where scale of values is between 0 to 100.

IV. Result and Discussion

The experiment is a sequence of the dataset obtained see Fig. 9. The features that have been selected results are 6 (six), including age, marital, education, job, housing, and loan. LAPS captured from each feature and then convert to number value see Fig. 13. The borrowers get value (Loan Risk, Activity, and Profile score) from an example dataset. The Social Recommendation score will get by the other user as Recommenders.

	age	marital	education	job	housing	loan
0	30	married	basic.9y	blue-collar	yes	no
1	39	single	high.school	services	no	no
2	25	married	high.school	services	yes	no
3	38	married	basic.9y	services	unknown	unknown
4	47	married	university.degree	admin.	yes	no
5	32	single	university.degree	services	no	no
6	32	single	university.degree	admin.	yes	no
7	41	married	university.degree	entrepreneur	yes	no
8	31	divorced	professional.course	services	no	no
9	35	married	basic.9y	blue-collar	no	no
10	25	single	basic.6y	services	yes	no

Fig. 9. UCI Bank Marketing dataset

A. Result

This section describes the process splitting formula according to the dataset to obtain the selected suitable features.

1) Age and Marital status features selection in Fig. 10 (a), (b), have impact to ability to pay back the loan. Age and Marital status show the borrowers' family members and condition. Dataset shows distribution the range of age with percentage indicated in Fig. 10 (a). Age is the one important variable that also shows the productivity of the borrower. The Marital status dataset shows the list of status borrowers in Fig. 10 (b). Borrowers of productivity ages and single have the ability to pay installments on time.

	frequency	percentage
18-25	98	2.38%
26-29	314	7.63%
30-34	893	21.69%
35-39	801	19.45%
40-44	603	14.64%
45-49	493	11.97%
50-56	558	13.55%
57-60	249	6.05%
61-70	71	1.72%
71-88	38	0.92%

(a)

	frequency	percentage
unknown	11	0.27%
divorced	446	10.83%
single	1153	27.99%
married	2509	60.91%

(b)

Fig. 10. Percentage of Age (a) and Percentage of Marital Status (b)

2) Education and Job features selection is shown in Fig. 11 (a), (b), indicating the borrower candidate with a higher education level will get a good job position opportunity. The impact of education on salary changes significantly. The most substantial effect of education is also expressed at the highest level of education. Even under other factors, the dominant role of education on salary. The borrowers have higher education returns, particularly above the high school level. In general, we find that the higher the education in line with their salary growth.

	frequency	percentage
illiterate	1	0.02%
basic.4y	429	10.42%
professional.course	535	12.99%
basic.9y	574	13.94%
high.school	921	22.36%
university.degree	1264	30.69%
unknown	167	4.05%
basic.6y	228	5.54%

(a)

	frequency	percentage
unknown	39	0.95%
student	82	1.99%
technician	691	16.78%
housemaid	110	2.67%
unemployed	111	2.69%
blue-collar	884	21.46%
admin.	1012	24.57%
entrepreneur	148	3.59%
self-employed	159	3.86%
retired	166	4.03%
management	324	7.87%
services	393	9.54%

(b)

Fig. 11. Percentage of Education (a) and Percentage of Job (b)

3) Housing and Loan features selection are at greater risk of housing instability compared to homeowners in Fig.

12 (a), (b). Among the factors contributing to that risk are financial situations. Debt housing is riskier and far more likely than homeowners to pay more than 30 percent of their income in housing costs.

	frequency	percentage
unknown	105	2.55%
no	1839	44.65%
yes	2175	52.8%

(a)

	frequency	percentage
yes	665	16.14%
unknown	105	2.55%
no	3349	81.31%

(b)

Fig. 12. Percentage of Housing (a) and Percentage of the other Loan (b)

4) Borrower trustworthiness score presented the eligible borrowers after they have the trustworthiness score. The borrowers' trustworthiness score gives the borrowers scores after registering with a default value for the first time. It will increase the borrowers' activity in the lending process and activity in the payment process (on simulation). The recommenders can give excellent recommendations to borrowers who propose a loan. An essential part of the personal lending simulation is a recommendation that aims to reduce dependence on collateral.

$$\begin{aligned} Trustworthiness\ Score = {} & Loan\ Risk\ score \\ & + Activity\ score + Profile\ score \\ & + Social\ Recommendation\ score \end{aligned} \tag{4}$$

with:

- *Trustworthiness Score*: Borrower trustworthiness score.
- *Loan Risk score*: Information of the record from another loan of Borrower.
- *Activity score*: Business activity or job information of Borrower.
- *Profile score*: Personal information of Borrower.
- *Social Recommendation score*: The recommendation value of Borrowers from Recommender.

5) The LAPS formula is a commitment between borrowers, lenders/investors, and recommenders set by the smart contracts management so that all parties understand each other's obligations and risks that will be accepted. The variables include Loan Risk, Activity, Profile, and Social Recommendation. All data will be assessed as a borrowers' trustworthiness score (LAPS). LAPS formula, we add positive weight for each variable, in equation 5:

$$\begin{aligned} LAPS = {} & (w_l * Loan\ Risk\ score) \\ & + (w_a * Activity\ score) + (w_p * Profile\ score) \\ & + (w_s * Social\ Recommendation\ score) \end{aligned} \tag{5}$$

where $\{w\ in\, \mathbb{R} \mid w \leq 1\}$, and $w_l, w_a, w_p,\ and\ w_s$ are positive weights of the trustworthiness parameters such that $w_l + w_a + w_p + w_s = 1$. The weights of the trustworthiness attributes are predetermined based on their priority value that can modify by consensus. For example, $w_l = 0.25$, $w_a = 0.2$, $w_p = 0.25$, $w_s = 0.3$. In this example, the social recommendation is given the highest percentage, and activity is given the lowest value it shows that the social recommendation is the priority to measure the eligible borrower candidate. Equation 5 is the complete formula for trustworthiness score after weight added is supportive to imprecise conclusions. After they get

	age	job	marital	education	housing	loan
0	100	65	100	78	100	100
1	95	70	80	85	55	100
2	55	70	100	85	100	100
3	95	70	100	78	50	50
4	50	85	100	100	100	100
...	...	...	...	...	...	...
4114	100	85	100	71	100	55
4115	95	85	100	85	100	100
4116	55	55	80	85	55	100
4117	60	85	100	85	55	100
4118	100	90	80	85	100	100

4119 rows × 6 columns

Fig. 13. Converted Dataset Selection

the score (see in Fig. 13 and Fig. 14), they can propose some loans with their borrowers' trustworthiness score and determine the maximum loan. The borrowers' trustworthiness scores will increase alongside the track record of borrowers' payments. After converting the

	profile	activity	loanRisk	recommendation	Trust Score
0	80	65	100	0	0
1	78	70	66	0	0
2	72	70	100	0	0
3	79	70	50	0	0
4	78	85	100	0	0
...	...	...	...	...	...
4114	77	85	89	0	0
4115	82	85	100	0	0
4116	68	55	66	0	0
4117	73	85	66	0	0
4118	79	90	100	0	0

4119 rows × 5 columns

Fig. 14. Transform Dataset Selection

selection dataset, then grouping the features in line with the LAPS variables formula seen in Fig. 14, the features are mentioned in the splitting formula. We obtained the selection feature grouping. The experiment applied these features selected to a personal lending prototype. The first experimental results were seen in Fig. 15 show the borrowers trustworthiness score, and the first user obtains 79, following the other users, after the recommender gives the value in the prototype. The LAPS formula will compute the trustworthiness score.

Platform users

#	Borrower contract address	Borrower wallet address	Total TScore	Activity score	Profile score	Social recommendation score	Loan risk score	# cycles
0	0x61c36a8d610163660E21a8b7359e1Cac0C9133e1	0x90F79bf6EB2c4f870365E785982E1f101E93b906	79	65	80	73	100	1
1	0x8EFa1819Ff5B279077368d44B593a4543280e402	0x70997970C51812dc3A010C7d01b50e0d17dc79C8	74	70	78	82	66	1
2	0xA14d9C7a916Db01cCA55ec21Be1F7665C326928F	0x976EA74026E726554dB657fA54763abd0C3a0aa9	79	70	72	76	100	1
3	0x7fc1375aA5d360Ca90cc443B5c3d3919aA8B9208	0x15d34AAf54267DB7D7c367839AAf71A00a2C6A65	64	70	79	61	50	1

Fig. 15. LAPS result 1

Platform users

#	Borrower contract address	Borrower wallet address	Total TScore	Activity score	Profile score	Social recommendation score	Loan risk score	# cycles
0	0x61c36a8d610163660E21a8b7359e1Cac0C9133e1	0x90F79bf6EB2c4f870365E785982E1f101E93b906	88	100	88	73	100	1
1	0x8EFa1819Ff5B279077368d44B593a4543280e402	0x70997970C51812dc3A010C7d01b50e0d17dc79C8	75	70	80	82	66	1
2	0xA14d9C7a916Db01cCA55ec21Be1F7665C326928F	0x976EA74026E726554dB657fA54763abd0C3a0aa9	72	65	79	76	66	1
3	0x7fc1375aA5d360Ca90cc443B5c3d3919aA8B9208	0x15d34AAf54267DB7D7c367839AAf71A00a2C6A65	73	70	62	61	100	1

Fig. 16. LAPS result 2

The second experiment in Fig. 16 shows with different data tests (variables changes values), the result of borrower trustworthiness score are positive values. The prototype succeeded in computing the features selected with the LAPS formula. The system will automatically increase the value of the borrowers' trustworthiness score (LAPS). The borrower will be able to propose a more significant amount than before if their score rises. The borrower with a high trustworthiness score will be easier to propose loans with increasing loan plan limits in the next cycle. Smart contracts management at borrowers, lenders/investors, and recommenders sides will handle each functionality from the available services on the Ethereum blockchain. With the limitation of the available digital wallet account tests, the test runs per each account with the equal method for all datasets.

B. Discussion

Features selection is a part of choosing the best variable for supporting personal lending, and many features could be selected. Credit Scoring is the most important for selecting the best applicant with the minimum risk. Some features will help describe the conditions for the borrower to pay back the loan. On the other hand, lenders/investors cover their risk with these features, and their money can not return. First, features data will be compiled with the standard method, and the result will be analyzed combined with another method. Secondly, all features try to connect with others and choose the relevant features. The result will show how to adequate the relation between two features. Next, try to rank each feature with the highest score and follow the following score until finished.

The presented the LAPS formula the challenges and open problems previously discussed. The formula covers minimizing collateral when borrowers propose a loan. All variables (Loan risk, Activity, Profile, and Social recommendation score) support borrowers to get a loan from lenders/investors. The LAPS formula is well adapted to the personal lending platform to accommodate the recommenders and lenders/investors to decide.

V. Conclusion

This research aims to compute the trustworthiness score (LAPS) to provide a reliable borrower. The result obtained the selected features from UCI Bank Marketing public dataset with the highest impact factor weight. The variables in this context are the categorical type features converted to quantitative. The LAPS formula shows all borrowers' activity by referring to the personal lending prototype, which directly interacts among borrowers, recommenders, and lenders/investors. The LAPS model describes the scoring of trustworthiness that has been successfully applied to the personal lending prototype. Lenders can use the trustworthiness score to decide the eligible borrowers' candidates.

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References

[1] S. Arya, C. Eckel, and C. Wichman, "Anatomy of the credit score," *Journal of Economic Behavior and Organization*, vol. 95, no. 47783, pp. 175–185, 2013.

[2] R. Xu, X. Lin, Q. Dong, and Y. Chen, "Constructing trustworthy and safe communities on a blockchain-enabled social credits system," *ACM International Conference Proceeding Series*, pp. 449–453, 2018.

[3] D. Roman and G. Stefano, "Towards a reference architecture for trusted data marketplaces: The credit scoring perspective," *Proceedings - 2016 2nd International Conference on Open and Big Data, OBD 2016*, pp. 95–101, 2016.

[4] G. Capital, "Unsecured Business Loans Without Collateral," 2018. [Online]. Available: https://gudcapital.com/unsecured-business-loans-without-collateral/

[5] W. Uriawan., O. Hasan., Y. Badr., and L. Brunie., "Collateral-free trustworthiness-based personal lending on a decentralized application (dapp)," in *Proceedings of the 18th International Conference on Security and Cryptography - SECRYPT,*, INSTICC. SciTePress, 2021, pp. 839–844.

[6] S. Moro, P. Cortez, and P. Rita, "A data-driven approach to predict the success of bank telemarketing," *Decision Support Systems*, vol. 62, pp. 22–31, 2014. [Online]. Available: https://doi.org/10.1016/j.dss.2014.03.001

[7] G. Bennouna and M. Tkiouat, "Scoring in microfinance: Credit risk management tool -Case of Morocco-," *Procedia Computer Science*, vol. 148, no. Icds 2018, pp. 522–531, 2019.

[8] A. Trabelsi, Z. Elouedi, and E. Lefevre, "Decision tree classifiers for evidential attribute values and class labels," *Fuzzy Sets and Systems*, vol. 366, pp. 46–62, 2019. [Online]. Available: https://doi.org/10.1016/j.fss.2018.11.006

[9] I. Brown and C. Mues, "An experimental comparison of classification algorithms for imbalanced credit scoring data sets," *Expert Systems with Applications*, vol. 39, no. 3, pp. 3446–3453, 2012. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2011.09.033

[10] J. Wang, K. Guo, and S. Wang, "Rough set and tabu search based feature selection for credit scoring," *Procedia Computer Science*, vol. 1, no. 1, pp. 2425–2432, 2010, iCCS 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050910002747

[11] W. Uriawan, A. Wahana, C. Slamet, and V. Suci Asih, "A dapp architecture for personal lending on blockchain," in *2021 7th International Conference on Wireless and Telematics (ICWT)*, 2021, pp. 1–6.

[12] D. Martens, M. De Backer, R. Haesen, J. Vanthienen, M. Snoeck, and B. Baesens, "Classification with ant colony optimization," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 5, pp. 651–665, Oct 2007.

[13] S. Kellison and R. London, *Risk Models and Their Estimation*, ser. ACTEX academic series. ACTEX Publications, 2011. [Online]. Available: https://books.google.fr/books?id=JvmZTcRTQ6cC