CREDIT SCORE & AGING ANALYSIS

JULY 29, 2019

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Overview

Goals & Challenges

PT. X is a subsidiary company from PT. Y and founded in 2017. We are a financial technology company and registered under Indonesian Financial Services Authority (OJK – *Otoritas Jasa Keuangan*). We mainly focus on peer to peer microlending with a mobile application. Simply, this app will connect between lenders and borrowers.

Our goal is to help unbanked people to receive microloans by providing seamless experience and eliminating conventional banks requirements which allow them to receive the microloans within a short period of time. This will give an ease to borrowers who have not had a chance to receive loan from conventional banks in the past and encourage them to build or to expand their business. This will stimulate microbusinesses and improve their quality of lives hence.

Serving the unbanked remains challenge. We believe by intertwining the notion of helping the poor and micro-investing, it raises awareness to improve the social welfare of certain communities across Indonesia. This breakthrough is a win-win solution for lenders and borrowers. Borrowers will be able to receive their money without a hassle. While, lenders can invest their money as low as IDR 3,300,000 (or equivalent to USD 230) with an annual return rate starting from 8% to 14% —depending on the borrowers' EKF credit score. In comparison to traditional investment companies in Indonesia, a minimum investment amount is IDR 250,000,000 (or equivalent to USD 17,500). Consequently, this would stimulate young adults between 20 to 30 years old to start investing their money for the greater goods.

In this project scope, we will (1) analyze and enhance the current credit score system, (2) measure our performance by predicting the credit score, and (3) find the average aging point that should be flagged as bad debt. The greatest challenge is all our borrowers are filtered from the parent company; so, it is already bias, and we are learning a certain favorable group.

"Building communities without poverty"

A Glimpse of Borrowers' Background

Data Exploration

As we are trying to be independent from the parent company, it is crucial for us to learn the characteristics of our future borrowers by learning Y's borrowers. We will examine in detail what are the key takeaways from this observation.

In *Table 1*, the summary statistics shows the average of loan amount, interest rate, and maturity. The average loan amount is IDR 3,813,108 (or equivalent to $268), the average interest rate is 12.03%, the average maturity is 39.46 weeks, the average length of business ownership is 75.18 months, and the average length of stay is 21.12 months.

	Loan Amount	Interest [%]	Maturity	Length of Business Ownership	Length of Stay
count	7.377000e+03	7377.000000	7377.000000	7377.000000	7377.000000
mean	3.813108e+06	12.029822	39.425918	75.183543	21.116307
std	6.365609e+05	0.932616	2.883864	80.365198	14.866352
min	2.300000e+06	8.000000	25.000000	1.000000	0.000000
25%	3.360000e+06	12.000000	40.000000	24.000000	8.000000
50%	3.860000e+06	12.000000	40.000000	48.000000	20.000000
75%	4.360000e+06	12.000000	40.000000	96.000000	30.000000
max	6.650000e+06	15.000000	50.000000	876.000000	110.000000

Table 1. Summary Statistics

In *Table 2*, majority of our borrowers' credit score is B, followed by B+, and C+. In fact, borrowers' who have A+, A, and A- score are quite small.

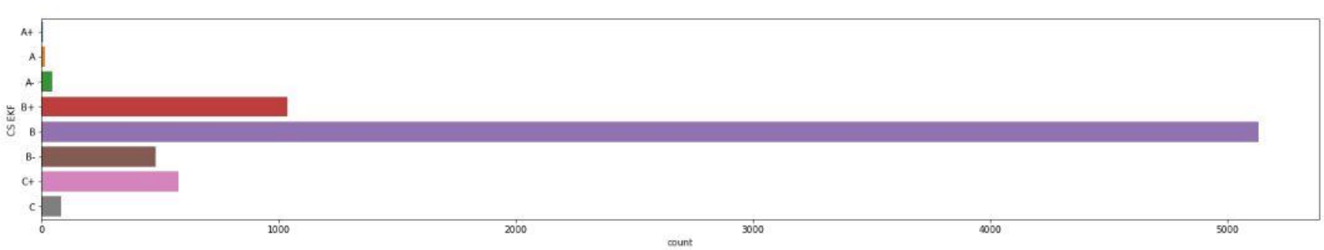

Table 2. Distribution of Borrowers' EKF Credit Score

In *Table 3*, borrowers' credit score will exert influence on their interest rate.

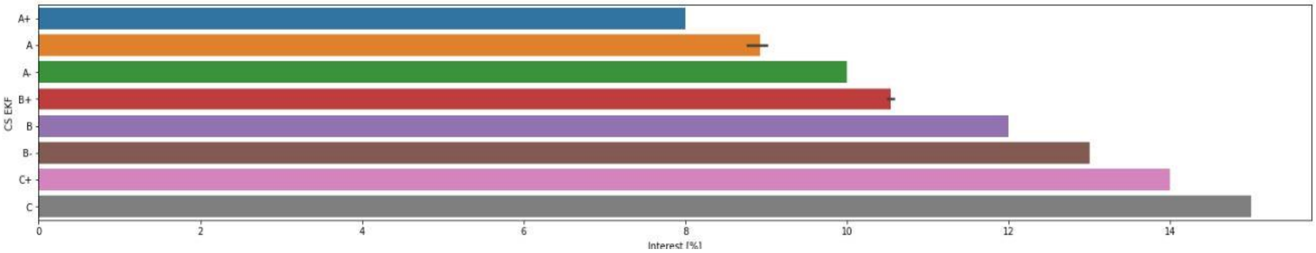

Table 3. Average Borrowers' Interest Rate Based on Their Credit Score

In *Table 4*, majority of our borrowers have trading business. The second highest is service; third, agriculture; fourth, farming, and lastly, industry.

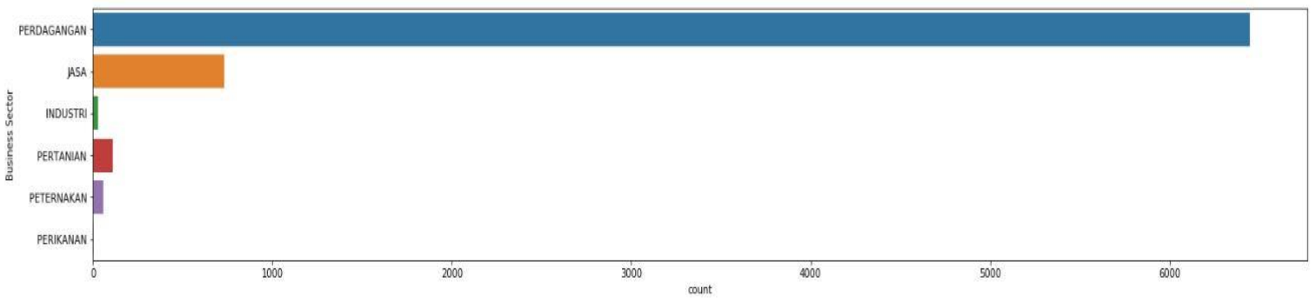

Table 4. Borrowers' Business Sector

In *Table 5*, most our clients choose 40 weekly payments instead 25 bi-weekly payments.

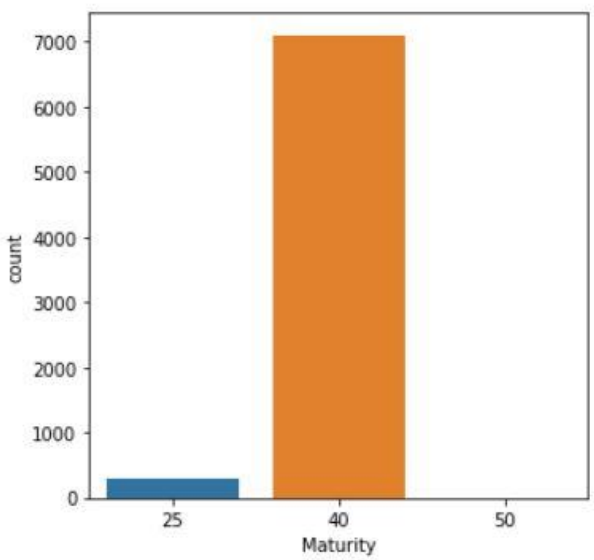

Table 5. Maturity

In *Table 6*, all our borrowers are female.

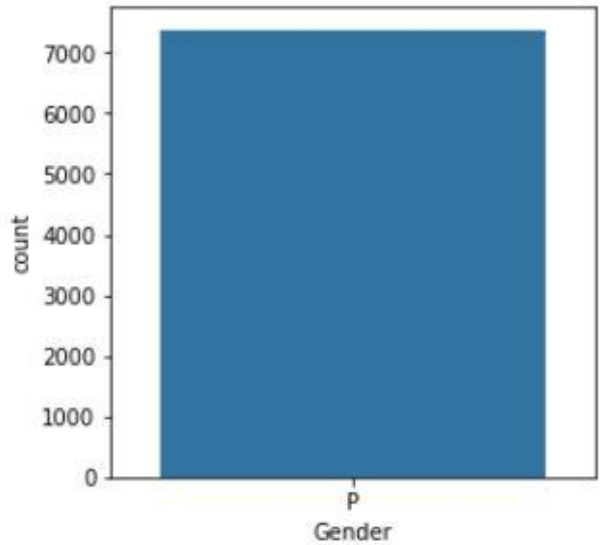

Table 6. Gender

In Table 7, there are six elements that influence a credit score: (1) length of stay, (2) home ownership, (3) maturity, (4) length of business ownership, (5) maturity status, and (6) loan amount.

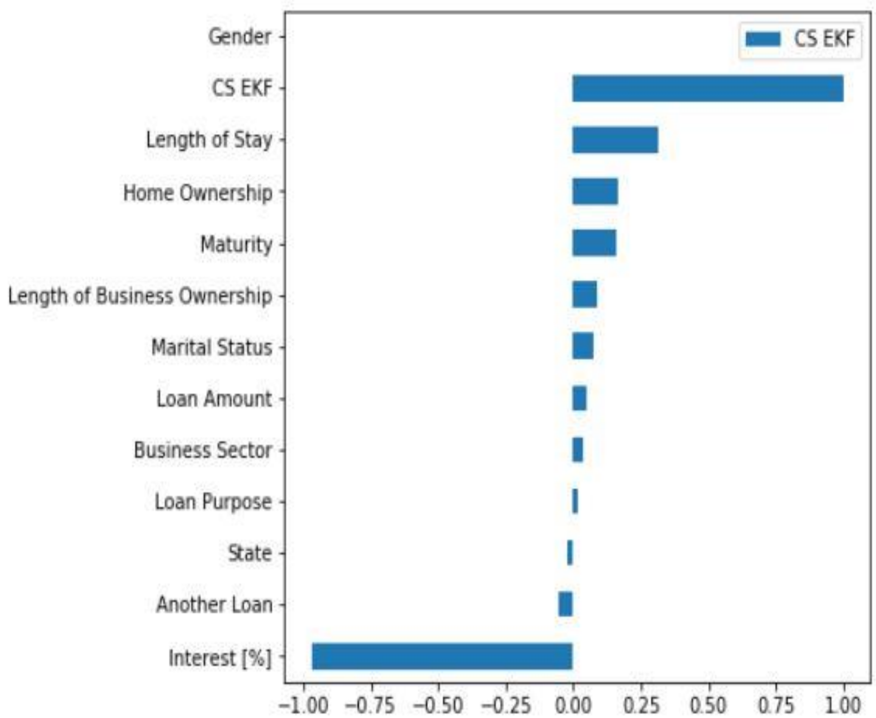

Table 7. Features Ranking that Influence a Credit Score

In *Table 8*, we are performing a correlation graph to find in detail which variables are connected.

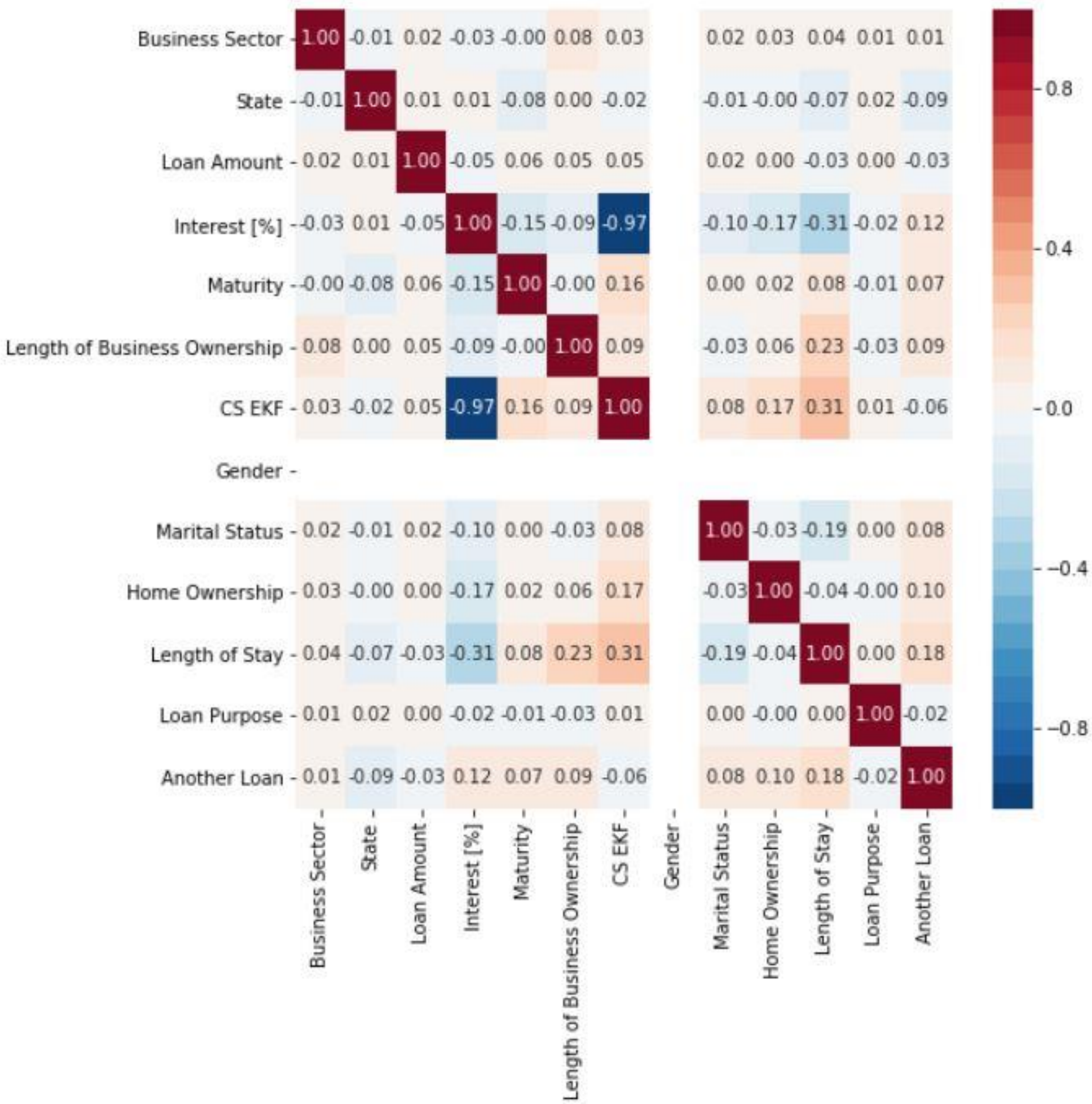

Table 8. Correlation Graph

Have we been measuring the credit score accurately?

Machine Learning Algorithms

In general, 1% to 2% of our borrowers are having non-performing loan (NPL). Even though this number is healthy, we would like to examine further whether we have been measuring our borrowers' credit score properly.

We will run four different machine algorithms to measure our performance. Those are K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Gradient Boosting, and Random Forest.

K-Nearest Neighbors (KNN)

KNN is a supervised learning algorithm in which one that relies on labeled input data to learn a function that produces a suitable output when given new unlabeled data. This algorithm captures the notion of similarity.

Table 9 shows we can predict 69.28% of the credit score correctly. It appears that precision, recall, and f-1 score have low variance specifically Group 5 (A-), Group 6 (A), and Group 7 (A+) have null value.

	precision	recall	f1-score	support
0	0.20	0.02	0.04	85
1	0.55	0.22	0.32	576
2	0.38	0.08	0.13	482
3	0.71	0.95	0.82	5133
4	0.28	0.05	0.09	1036
5	0.00	0.00	0.00	46
6	0.00	0.00	0.00	13
7	0.00	0.00	0.00	6
micro avg	0.69	0.69	0.69	7377
macro avg	0.27	0.17	0.17	7377
weighted avg	0.61	0.69	0.61	7377

The average is 0.6928290633048665

Table 9. KNN Score Results

In *Table 10*, y-axis is predicted value and x-axis is actual value. For example, we scored 43 borrowers an A-, but in fact it is predicted to be a B+.

	A+	A	A-	B+	B	B-	C+	C
A+	2	19	5	59	0	0	0	0
A	3	127	12	431	3	0	0	0
A-	0	10	38	431	3	0	0	0
B+	5	72	43	4892	121	0	0	0
B	0	1	3	980	52	0	0	0
B-	0	0	0	42	4	0	0	0
C+	0	0	0	11	2	0	0	0
C	0	0	0	6	0	0	0	0

Table 10. KNN Confusion Matrix

In *Table 11*, it is a confusion matrix heatmap. We would like to see how the predicted value and actual value are distributed. This gives us a notion how well our model is. This concludes that our model is somehow inappropriate in predicting a borrower's credit score. Yet, the more diagonal of the graph, the better the model is.

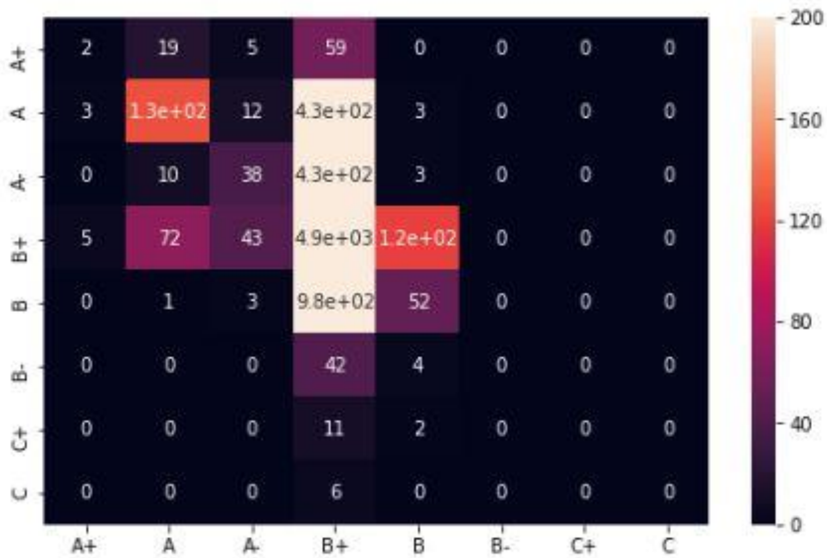

Table 11. KNN Heatmap

Support Vector Machine (SVM)

SVM is a supervised learning algorithm that finds a hyperplane in an N-dimensional space (N – the number of features) that clearly classifies the data points.

Table 12 shows we can predict 71.70% of the credit score correctly. Similar like KNN, the score is not distributed properly. There are three groups who have null value that has caused the macro average results very low.

```
              precision    recall  f1-score   support

           0       0.67      0.02      0.05        85
           1       0.83      0.20      0.32       576
           2       0.50      0.06      0.10       482
           3       0.72      0.98      0.83      5133
           4       0.60      0.11      0.18      1036
           5       0.00      0.00      0.00        46
           6       0.00      0.00      0.00        13
           7       0.00      0.00      0.00         6

   micro avg       0.72      0.72      0.72      7377
   macro avg       0.41      0.17      0.19      7377
weighted avg       0.69      0.72      0.64      7377

The average is 0.7169581130540871
```

Table 12. SVM Score Results

In *Table 13*, it is less scattered compared to the KNN confusion matrix, but it appears that we still make some errors in predicting our borrowers' credit score. For example, we scored 18 borrowers an A-, but it is predicted to be a B+.

	A+	A	A-	B+	B	B-	C+	C
A+	2	13	0	70	0	0	0	0
A	0	116	8	452	0	0	0	0
A-	1	1	27	452	1	0	0	0
B+	0	10	18	5033	72	0	0	0
B	0	0	1	924	111	0	0	0
B-	0	0	0	44	2	0	0	0
C+	0	0	0	13	0	0	0	0
C	0	0	0	6	0	0	0	0

Table 13. SVM Confusion Matrix

In Table 14, the distribution of SVM confusion matrix heatmap is like the KNN. It is somehow focused on the center and not diagonal.

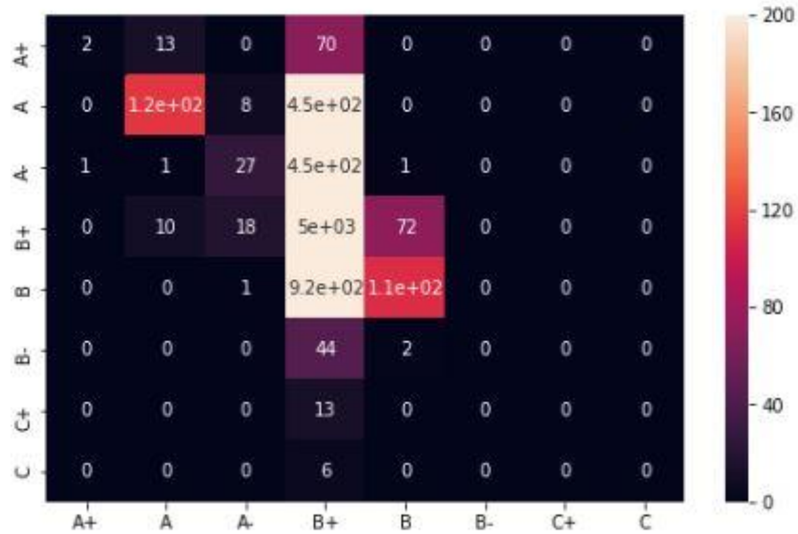

Table 14. SVM Heatmap

Gradient Boosting (GB)

Gradient Boosting is very popular among data scientists. It uses boosting method of converting weak learners into strong learners. Simply, the weighted sum of the predictions made by the previous tree models.

Table 15 shows we can predict 99.34% of the credit score correctly. It appears that precision, recall, and f-1 score are well distributed; however, there is a little instability of Group 5 (A-) where they have the lowest scores among other groups.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	85
1	1.00	1.00	1.00	576
2	1.00	1.00	1.00	482
3	1.00	1.00	1.00	5133
4	0.97	0.99	0.98	1036
5	0.46	0.26	0.33	46
6	1.00	0.85	0.92	13
7	0.86	1.00	0.92	6
micro avg	0.99	0.99	0.99	7377
macro avg	0.91	0.89	0.89	7377
weighted avg	0.99	0.99	0.99	7377

The average is 0.9933577334960011

Table 15. Gradient Boosting Score Results

In *Table 16*, it shows that we are nearly predict the credit score perfectly. For example, we scored 33 borrowers a B, but it is predicted to be a B-.

	A+	A	A-	B+	B	B-	C+	C
A+	84	1	0	0	0	0	0	0
A	0	576	0	0	0	0	0	0
A-	0	0	482	0	0	0	0	0
B+	0	0	0	5133	0	0	0	0
B	0	0	0	0	1031	5	0	0
B-	0	0	0	0	33	13	0	0
C+	0	0	0	0	0	0	13	0
C	0	0	0	0	0	0	1	5

Table 16. Gradient Boosting Confusion Matrix

In *Table 17*, the distribution pattern is nearly diagonal. It shows that we make minimum error in determining our borrowers' credit score. It is a very good indicator that our credit score model is credible.

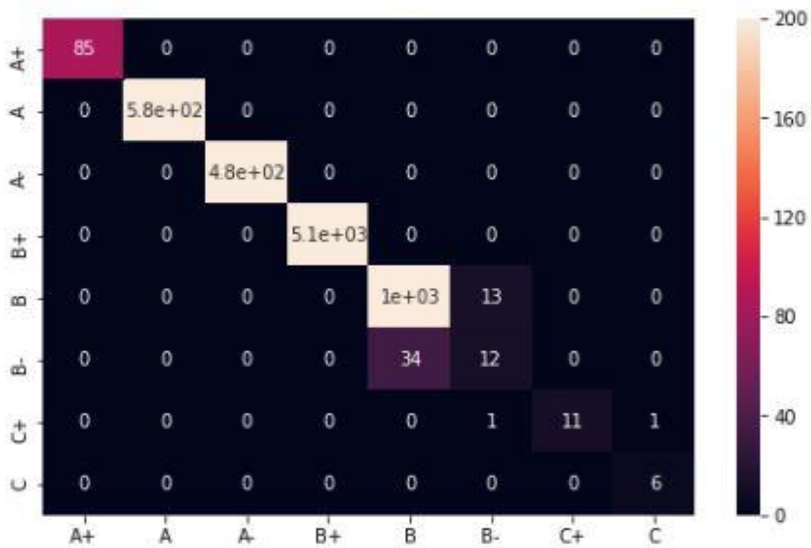

Table 17. Gradient Boosting Heatmap

Random Forest (RF)

Random Forest consists of multiple random decision tress. It trains each tree independently using a random sample of the data. Thus, it creates a more robust model and less likely to overfit on the training data.

Table 18 shows we can predict 99.46% of the credit score correctly. Even though most of the categorical groups scored nearly 1.00, Group 5 (A-) has the lowest overall score.

	precision	recall	f1-score	support
0	1.00	0.99	0.99	85
1	1.00	1.00	1.00	576
2	1.00	1.00	1.00	482
3	1.00	1.00	1.00	5133
4	0.97	1.00	0.98	1036
5	0.75	0.26	0.39	46
6	0.93	1.00	0.96	13
7	1.00	0.83	0.91	6
micro avg	0.99	0.99	0.99	7377
macro avg	0.96	0.88	0.90	7377
weighted avg	0.99	0.99	0.99	7377

The average is 0.9945777416293886

Table 18. Random Forest Score Results

In *Table 19*, the confusion matrix shows that our credit score model is credible –the fact that there is a minimum error. For example, there are 33 people we scored B, but it predicted to be a B-.

	A+	A	A-	B+	B	B-	C+	C
A+	84	1	0	0	0	0	0	0
A	0	576	0	0	0	0	0	0
A-	0	0	482	0	0	0	0	0
B+	0	0	0	5133	0	0	0	0
B	0	0	0	0	1031	5	0	0
B-	0	0	0	0	33	13	0	0
C+	0	0	0	0	0	0	13	0
C	0	0	0	0	0	0	1	5

Table 19. Random Forest Confusion Matrix

In *Table 20*, it looks the graph pattern nearly diagonal which just the same as gradient boosting. This indicates that our credit score model is nearly appropriate.

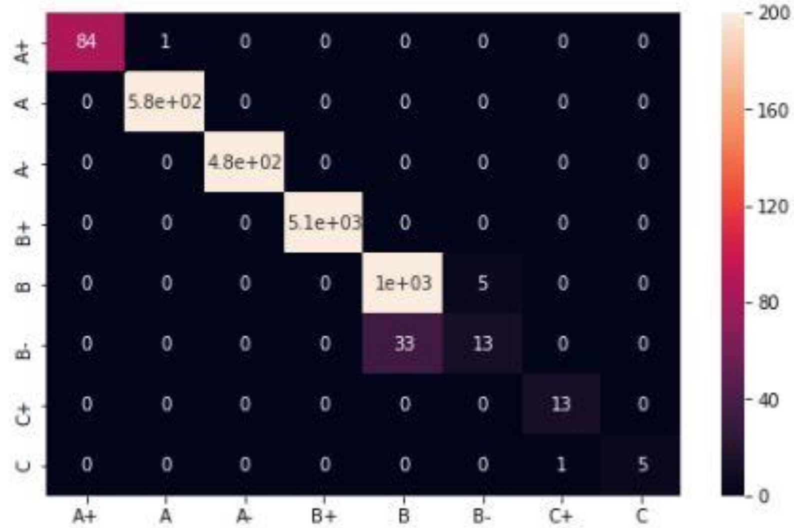

Table 20. Random Forest Heatmap

Bad Debt

Average aging (in days) that should be considered as red flag

In *Table 21*, there are four stages of past due category: (1) Stage 1 is 0-30 days, (2) Stage 2 is 40 days past due, (3) Stage 3 is 90 days past due, and (4) Stage 4 is 120 – 180 days past due.

It shows that nearly 2% of non-performing loan. We can conclude within 40 to 50 days past due should be considered as red flag since there is a high chance of non-performing loan.

Past Due Category	count	mean	std	min	25%	50%	75%	max
Kurang Lancar	12.0	49.500000	9.337120	40.0	41.00	46.5	57.25	64.0
Lancar	6803.0	0.122299	0.763610	0.0	0.00	0.0	0.00	16.0
Macet	113.0	152.893805	27.539051	98.0	133.00	154.0	173.00	233.0
Tidak Lancar	6.0	81.666667	6.947422	72.0	77.75	83.0	83.75	92.0

Table 21. Past Due Category

Note: Lancar – Stage 1, Kurang Lancar – Stage 2, Tidak Lancar – Stage 3, Macet – Stage 4

In *Table 22*, it seems province domicile, branch, city, and outstanding payment (*sisa pokok*) are related to aging. There could be many factors why province domicile influence aging such as socioeconomic factors (e.g. education, employment, and income).

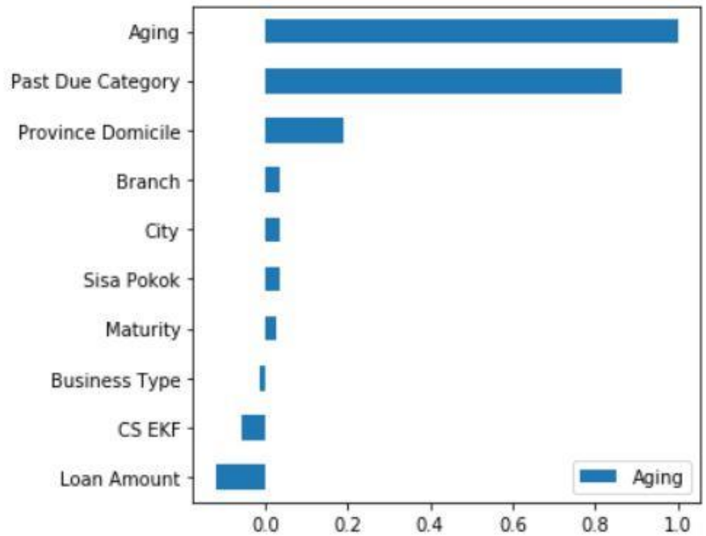

Table 22. Features Ranking that Influence Aging

In *Table 23*, there are 11 branches that have most distributed aging in days. The top three lowest performance are Perumnas, KCP Cisoka, and Kendari.

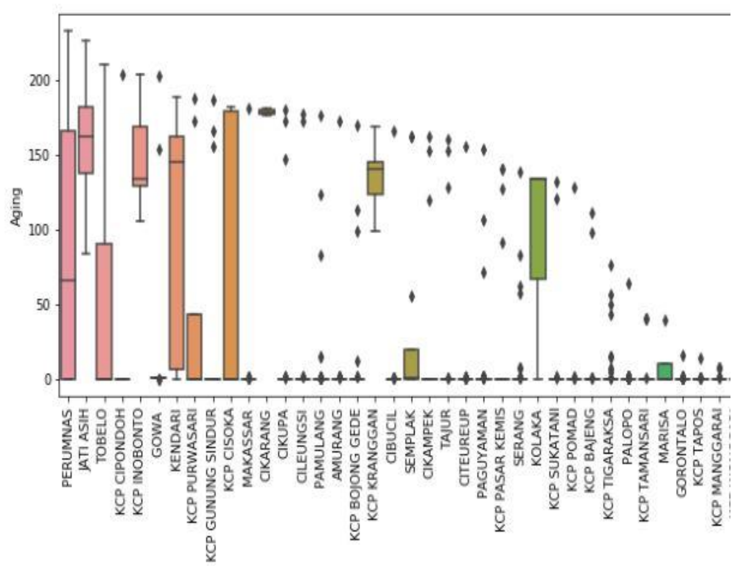

Table 23. Distribution Aging in days Based on Branch

In *Table 24*, the top five branches that have the high average aging in days are Cikarang, Jati Asih, KCP Inobonto, KCP Kranggan, and Kendiri.

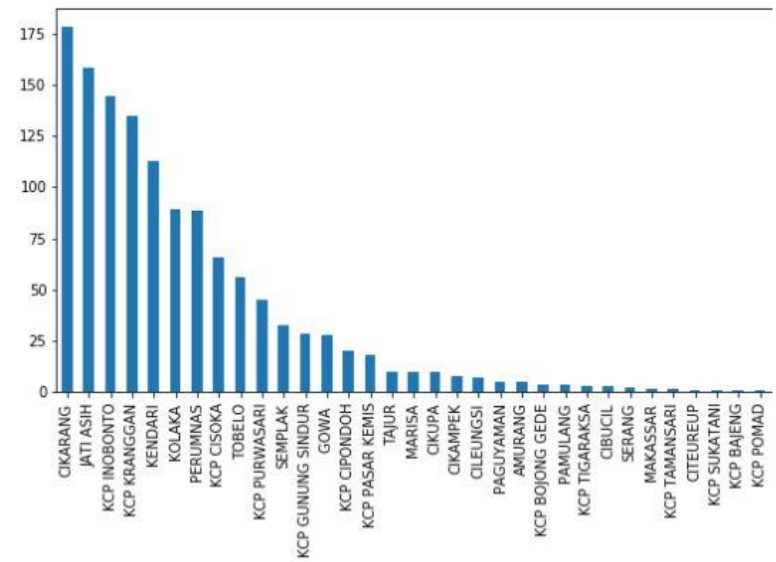

Table 24. Average Aging in days Based on Branch

Conclusion & Strategic Recommendations

Comparing all machine learning algorithms that we have used to measure our credit score model, we have decided to move forward with GB and RF –the fact that the overall scores are more variated than KNN and SVM which gives more credibility. It has come up to our attention that one of GB and RF score results are scored lowered than the others that is Group 5 (A-). For example, in RF, recall (0.26) and f-1 score rate (0.39); while in GB, precision (0.46), recall (0.26), and f-1 score rate (0.33) are fall under 0.50.

On the contrary, we are processing data that less than 10,000. This means our borrowers have been carefully selected from the parent company. The main reason we are doing this is we would like to minimize non-performing loan (NPL) in the future by learning the customers' behavior characteristics before we are going to become to public.

There are four recommendations that we would like to provide. First, as we have gained tremendous insights of building a credible credit score, we can apply the new credit score to the current borrowers and retesting the model with machine algorithms. If the new scores are more stable, we shall implement the new credit score moving forward. Second, we should consider a red flag if borrowers have past due within 40 to 50 days –the fact that there is a high probability of non-performing loan in the future. Third, we want to learn the socioeconomic factors based on province domicile and analyze the branch performance individually. Lastly, we can a create a new strategy with PT. Z For example, we lend loan to Z clients since Z creates platform that transform online to offline kiosk. Let's say, if a borrower needs an instant funding, X is only solution for them. Thus, we can obtain a vast amount of data that we can monetize in the future.

Suggested New Credit Score

Bobot	Kriteria	Nilai Credit Scoring	Nilai
5%	STATUS USAHA	MEMULAI USAHA BARU	4
		MENAMBAH MODAL USAHA	5
5%	LAMA USAHA	< 1 Bulan	3
		1 s.d 12 Bulan	4
		> 12 Bulan	5
10%	ANGSURAN LAIN	YES	8
		NO	10
35%	TEMPAT TINGGAL	SEWA/KONTRAK	21
		MILIK KELUARGA	28
		MILIK SENDIRI	35
25%	LAMA TINGGAL	< 1 Tahun	15
		1 s.d 10 Tahun	20
		> 10 Tahun	25
15%	STATUS KAWIN	SINGLE	9
		JANDA/DUDA	12
		MARRIED	15
5%	NILAI PINJAMAN	< 4 Juta	3
		4 - 5 Juta	4
		> 5 Juta	5

Credit Score	Range Nilai
A	100
B+	98-99
B	84-97
C	70-83

Table 25. Old Credit Score

Percentage	Criteria
35%	LAMA TINGGAL
25%	TEMPAT TINGGAL
15%	LAMA USAHA
10%	STATUS KAWIN
10%	ANGSURAN LAIN
5%	NILAI PINJAMAN

Table 26. New Credit Score