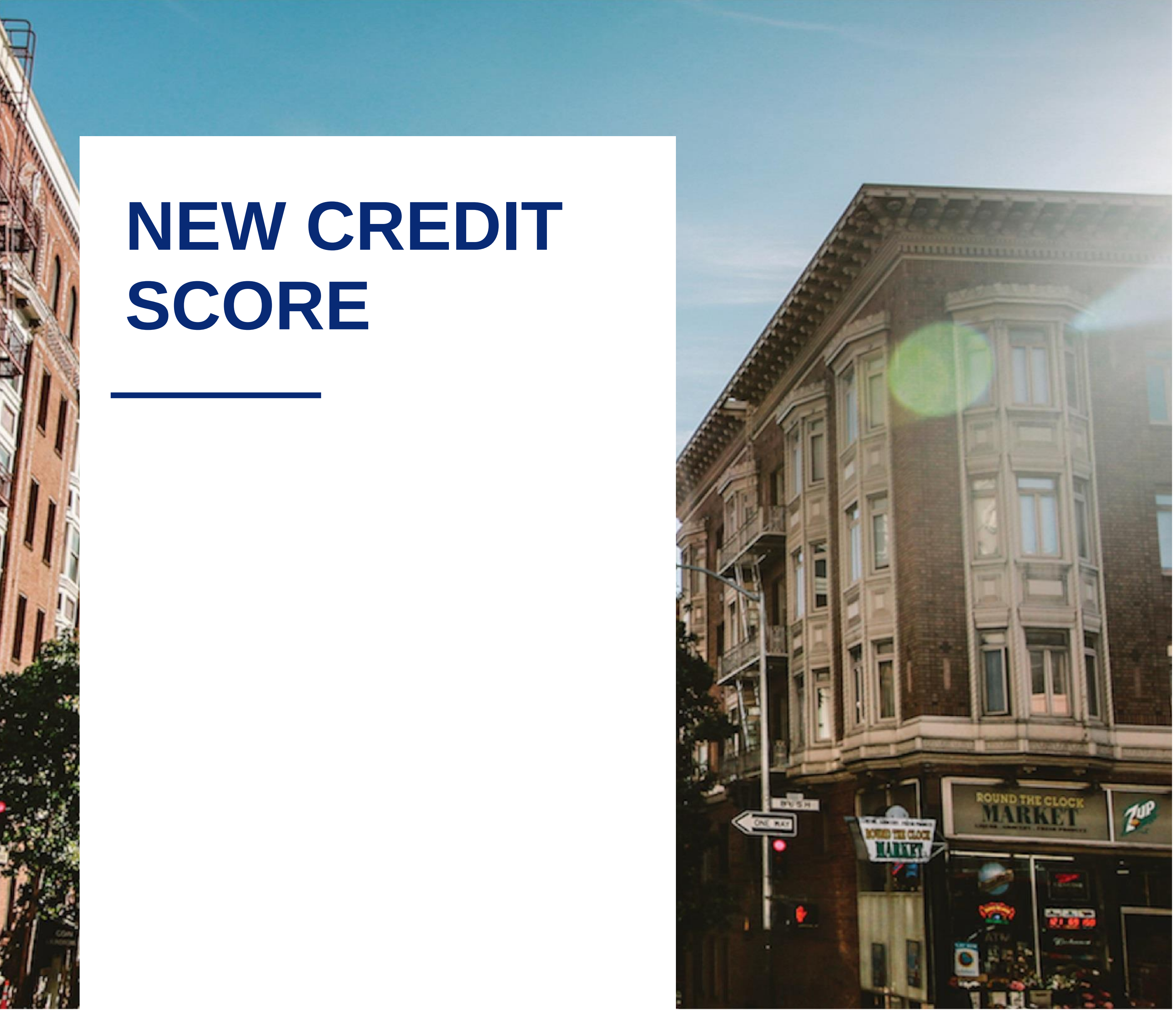

NEW CREDIT SCORE

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Overview

Goals and Challenges

In the previous project, we were trying to measure how well our credit score model. As we are choosing to move with Random Forest and Gradient Boosting, it has come up to our attention that there is a group that scores below average than the others. This indicates our model might have a chance of instability.

With the help of machine learning algorithms, we have reapplied the suggested credit score and so we would like to retest the performance of it. If the overall results will have better performance, we will implement the new credit score immediately.

The main challenge is we are testing data that is less than 10,000 –the fact that total of EKF borrowers is 7,332. Regardless the score results might be favorable to a certain group, this finding should be considered a guidance of building a credible credit score.

"Building communities without poverty"

Challenging the Current Credit Score

Data Exploration and Machine Learning Algorithms

We will analyze the new correlation graph and features ranking after applying the suggested new credit score (see *Table 1* and *Table 2*) as well as the average score results of Random Forest and Gradient Boosting.

In *Table 1*, the correlation table score is more enhanced than the previous one. In fact, it gives higher contrast to analyze the data.

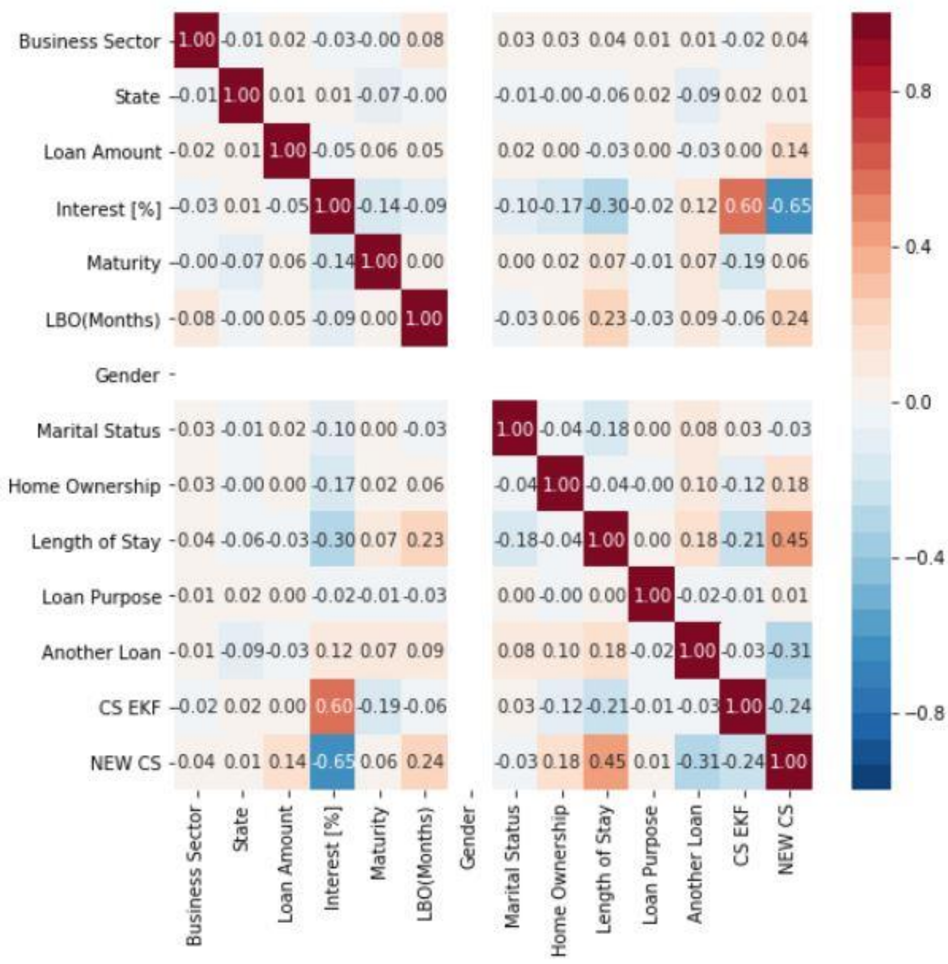

Table 1. Correlation Graph

In *Table 2*, features ranking is more enhanced as well. We can say there are five elements that we can use for the new credit score. Those are length of stay, length of business (in months), home ownership, loan amount, and another loan/other loans.

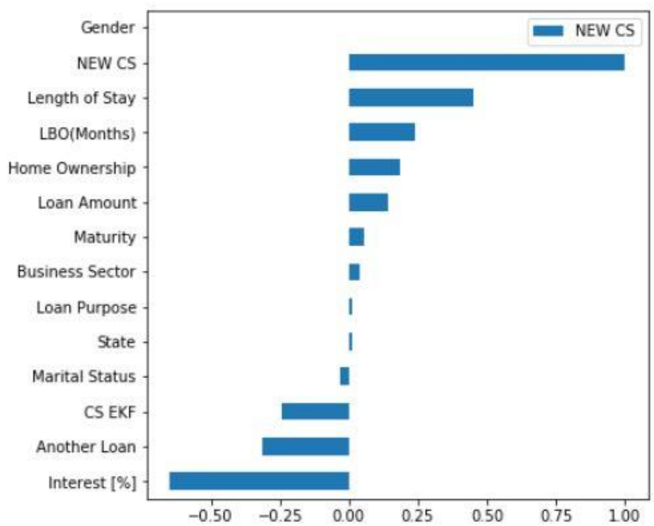

Table 2. Features Ranking that Influences a Credit Score

In *Table 3*, we have formulated a suggested new credit score based on the correlation and features ranking that influence a credit score.

Bobot	Kriteria	Nilai Credit Scoring	Nilai
35%	Lama Tinggal	< 1 Tahun	21
		1 s.d 10 Tahun	28
		> 10 Tahun	35
25%	Tempat Tinggal	SEWA/KONTRAK	15
		MILIK KELUARGA	20
		MILIK SENDIRI	25
15%	Lama Usaha	< 1 Bulan	5
		1 s.d 12 Bulan	10
		> 12 Bulan	15
10%	Angsuran Lain	YES	5
		NO	10
10%	Status Kawin	SINGLE	6
		JANDA/DUDA	8
		KAWIN	10
5%	Nilai Pinjaman	>= 3,300,000 s/d < 4,300,000	3
		>= 4,300,000 s/d < 5,300,000	4
		>= 5,300,000	5

Table 3. Suggested New Credit Score

Gradient Boosting (GB)

Table 4 shows we can predict 98.98% of the credit score correctly. Even though the previous model has slightly higher score by 0.36%, the new scores are evenly distributed and there is no single score that fall below 0.50. Indeed, the lowest score is recall (0.75) in Group 7 (A+). Recall is the total percentage relevant results correctly classified by the algorithm.

	precision	recall	f1-score	support
0	0.99	0.96	0.97	338
1	0.99	0.99	0.99	1959
2	0.99	0.99	0.99	1341
3	0.99	1.00	0.99	2654
4	0.99	0.98	0.98	457
5	0.99	0.99	0.99	436
6	0.95	0.95	0.95	135
7	0.90	0.75	0.82	12
micro avg	0.99	0.99	0.99	7332
macro avg	0.97	0.95	0.96	7332
weighted avg	0.99	0.99	0.99	7332

The average is 0.9897708674304418

Table 4. Gradient Boosting Score Results

In *Table 5*, the confusion matrix is distributed very well. We can see there is still a slight mistake that we are making. For example, we scored 14 borrowers A, but in fact it is predicted to be a A+.

	A+	A	A-	B+	B	B-	C+	C
A+	324	14	0	0	0	0	0	0
A	3	1943	9	2	2	0	0	0
A-	0	1	1333	6	0	1	0	0
B+	0	2	1	2642	2	1	6	0
B	0	0	0	8	447	1	0	1
B-	0	0	0	5	0	431	0	0
C+	0	0	0	7	0	0	128	0
C	0	0	0	0	2	0	1	9

Table 5. Gradient Boosting Confusion Matrix

In *Table 6,* the graph patterns are more enhanced and distributed very well than the previous model. We can say it is close-enough to be diagonal.

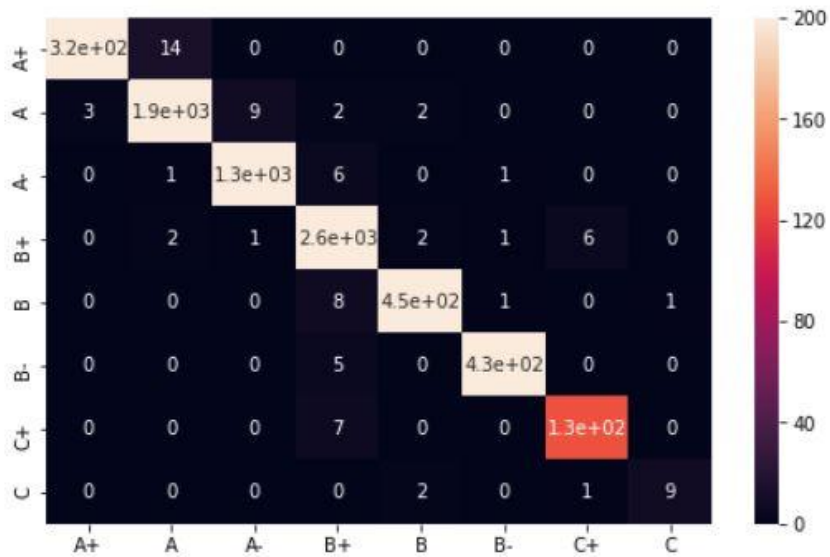

Table 6. Gradient Boosting Heatmap

Random Forest

Table 7 shows we can predict 98.83% of the credit score correctly. Even though the previous model has slightly higher score by 0.64%, the new scores look more stable and there is no single score that fall below 0.50. Indeed, the lowest score is recall (0.83) in Group 7 (A+).

	precision	recall	f1-score	support
0	0.98	0.91	0.95	338
1	0.99	0.99	0.99	1959
2	0.99	0.99	0.99	1341
3	0.99	1.00	0.99	2654
4	0.98	0.98	0.98	457
5	0.98	1.00	0.99	436
6	1.00	1.00	1.00	135
7	0.91	0.83	0.87	12
micro avg	0.99	0.99	0.99	7332
macro avg	0.98	0.96	0.97	7332
weighted avg	0.99	0.99	0.99	7332

The average is 0.9882705946535734

Table 7. Random Forest Score Results

In *Table 8*, the distribution of the matrix is very similar to the Gradient Boosting. It seems the number of errors in RF confusion matrix is slightly higher. For example, we scored 29 borrowers A, but it is predicted to be an A+.

	A+	A	A-	B+	B	B-	C+	C
A+	309	29	0	0	0	0	0	0
A	6	1932	10	9	2	0	0	0
A-	0	0	1333	6	2	0	0	0
B+	0	0	1	2646	3	4	0	0
B	0	0	0	5	447	4	0	1
B-	0	0	0	0	2	434	0	0
C+	0	0	0	0	0	0	135	0
C	0	0	0	0	1	1	0	10

Table 8. Random Forest Confusion Matrix

In *Table 9*, the heatmap pattern is nearly the same as RF heatmap. It is close-enough to be diagonal. This indicates our new credit score model is appropriate.

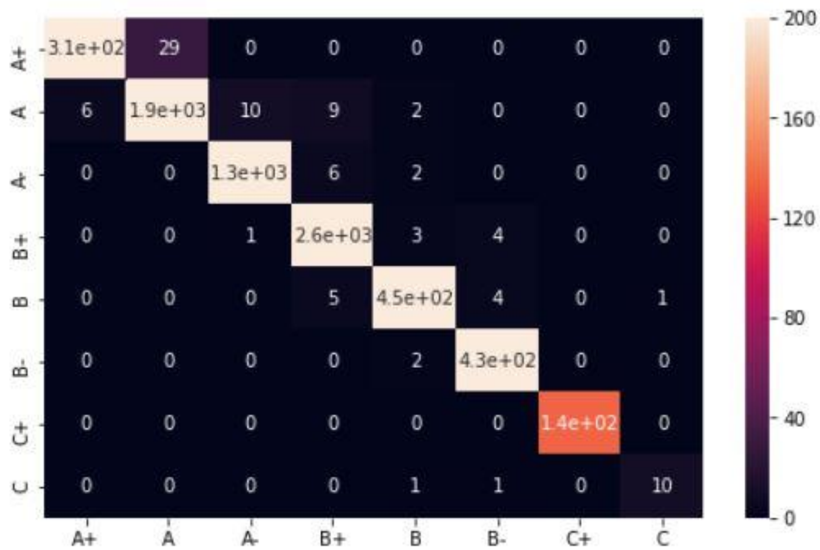

Table 9. Random Forest Heatmap

Conclusion & Strategic Recommendations

After analyzing the model from every aspect, we can confidently say that the suggested new credit score has convinced that it has better capability to measure a credible credit score for our borrowers. In fact, the score results of the new model have greater variations in terms of precision, recall, and f-1 score. Therefore, in average, we can predict 98% of a borrower's credit score correctly.

As the number of borrowers is growing by nearly 20% every year, we may want to maintain the quality of our model and continuously training/testing our data. This would help us to minimize bias, keep on track with data performance, and maintain data integrity. Yet, if there is an incongruity, we can take necessary action to remedy the issues.

This credit score will be effective as of August 15, 2019.