Northwestern MSDS-498 Artificial

Model #101: Credit Card Default Model

Model Development Guide

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1. Introduction

Credit risk modeling has advanced in the last several decades from local or collateral only based decisions to demographic and data-based industry. The features available for developing models has expanded while more data becomes available both at the individual and population levels. When these data are properly collected, cleaned and engineered to produce accurate predictions a bank can have an advantage and lend money with less risk producing hire profits.

2. The Data

University of California Irvine hosts a Machine Learning Repository (Dua and Graff 2019) which includes the default of credit card clients in Taiwan prepared to compare the predictive abilities of selected data mining methods (Dua and Graff 2019). The response variable of the dataset is a binary indicator for whether a customer defaulted on their credit card debt. Delinquency is defined as missing a single payment due date, while default is not making a specific number of consecutive payments (Cagan 2020). Entering default involves collections actions and likely losses for the creditor, so a company would seek customers unlikely to default.

The predictor variables included in the dataset can be divided into two categories about the customer: demographic attributes and billing/payment history. The demographic attributes are comprised of SEX, EDUCATION, MARRIAGE, and AGE. The billing/payment history variables comprise six months of history including repayment status, billing amount, and payment amount.

Before the data can be engineered into features consumable by different modeling methods, each datatype and feature class must be reviewed for sufficient and consistent data

quality. The dataset was first checked for empty values, and zero nullity was reported across all fields. The dataset was focused to only explanatory and target variables (ignoring the indices and those generated for splitting train/test/validate).

The data dictionary provides definitions and bounds for each variable and can be used to tell whether invalid values exist and must be cleaned. Appendix A provides the complete dictionary with each field explicitly defined.

Table 1: Data Dictionary - Abridged

Fields	Variable	Valid Values	
X1	LIMIT_BAL	> 0	Scalar positive
X2	SEX	(1,2)	Binary
X3	EDUCATION	(1:4)	Integer, categorical
X4	MARRIAGE	(1:3)	Integer, categorical
X5	AGE	Int, >0,<120	Discrete, potentially ordinal integer
X6-X11	PAY_#	(-1,1:9)	Discrete ordinal integer
X12-X17	BILL_AMT#	(1:3)	Scalar pos/neg
X18-X23	PAY_AMT#	(1:3)	Scalar positive
Z	DEFAULT	(0,1)	Binary

In order to understand the data as received and determine what cleaning and engineering steps are necessary, a high-level quality report assists in reviewing each variable's requirements & alignment to them. This was executed following the guidelines from Dempsey (2015).

Table 2: Data Quality Overview - Raw

Column Name	Data Type	Present Values	Missing Values	Unique Values	Minimum Value	Maximum Value
ID	int64	30000	0	30000	1	30000
LIMIT_BAL	int64	30000	0	81	10000	1000000
SEX	int64	30000	0	2	1	2
EDUCATION	int64	30000	0	7	0	6
MARRIAGE	int64	30000	0	4	0	3
AGE	int64	30000	0	56	21	79
PAY_0	int64	30000	0	11	-2	8
PAY_2	int64	30000	0	11	-2	8
PAY_3	int64	30000	0	11	-2	8
PAY_4	int64	30000	0	11	-2	8
PAY_5	int64	30000	0	10	-2	8
PAY_6	int64	30000	0	10	-2	8
BILL_AMT1	int64	30000	0	22723	-165580	964511
BILL_AMT2	int64	30000	0	22346	-69777	983931
BILL_AMT3	int64	30000	0	22026	-157264	1664089
BILL_AMT4	int64	30000	0	21548	-170000	891586
BILL_AMT5	int64	30000	0	21010	-81334	927171
BILL_AMT6	int64	30000	0	20604	-339603	961664
PAY_AMT1	int64	30000	0	7943	0	873552
PAY_AMT2	int64	30000	0	7899	0	1684259
PAY_AMT3	int64	30000	0	7518	0	896040
PAY_AMT4	int64	30000	0	6937	0	621000
PAY_AMT5	int64	30000	0	6897	0	426529
PAY_AMT6	int64	30000	0	6939	0	528666
DEFAULT	int64	30000	0	2	0	1

The data must be divided for the training and testing models in prediction of the target variable. Table 3 provides the counts of observations within each of the groups

Table 3: Data Modeling Splits

Group	Count
Train	15180
Test	7323
Validate	7497

3. Feature Engineering

In the practice of credit risk modeling, features are usually engineered by aggregating customer transactional data to determine behavioral patterns (Bahnsen et al 2016). We will also consider and test approaches for binning and combining demographic attributes of the customer, dependent on each specific model's needs.

The AGE attribute is received as integers indicating years of age for each customer. Because age is a discrete variable with high cardinality, discretization can bring it closer to a knowledge-level representation (Peng et al 2009) and is essential for models such as trees/forests. Age has been initially separated by decade, and testing will be performed on more evenly distributed bins or perhaps other approaches.

Table 4: Resulting distribution of Age Binning

Age_Group	Freq
1-10	0
11-20	0
21-30	11,013
31-40	10,713
41-50	6,005
51-60	1,997
61-70	257
71-80	15

Weight of evidence binning will also be tested, which divides the AGE attribute into four classes and the 'separation' of response results indicates that it will be a more effective means than based only on decade.

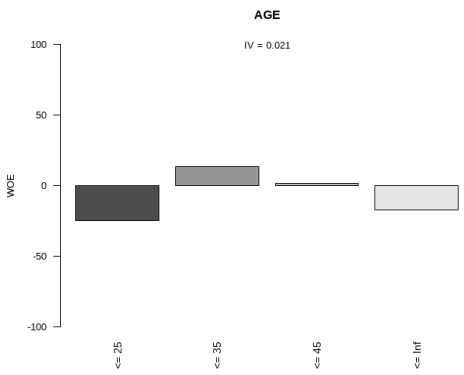


Figure 1: Weight of Evidence Binning Result - Age

In order to produce variables useful and potentially meaningful to statistical models, all transactional data will be replaced with aggregated and computed statistics.

- **Utilization** - balance divided by the consumer's credit line each month. The Values resulting are between approximately negative two and positive eleven. After averaging across all months to produce util_avg, these will be scaled between negative one and positive one, testing normalization first.

- **Payment_ratio** - payment each month divided by the previous month's balance. To be initially normalized between zero and one. Any month with zero balance will be set to one as this is a "perfect" payment; no remaining balance due. The average was calculated across all then the original time series values were dropped.

- **Age_bins** – Initial binning by decade; Weigh of Evidence has also been used and the two will be compared for performance/correlation with target.

- **Other binning** - Binning was also tested on the following categorical fields: PAY, education. Effect was minimal and often detrimental to model quality so it was abandoned

- **Sex, Education and Marriage** – categorial variables that after testing for minor engineering efforts resolved to remain as received

- **bill_max** – the maximum value across all month's bills

- **payment_max** – the maximum value across all months' payment values

- **pay_max** – each month's pay field indicates how delinquent a customer is. This field indicates the longest (highest value) that a customer has been delinquent in available history

Commented [AJS1]: Tbc

Commented [AJS2]: May need to be standardized due to high ratios seen

Commented [AJS3]: Need to implement and test

Commented [AJS4]: Need to test

4. Exploratory Data Analysis

After initial engineering of the data for feature generation, the distribution and key statistics of the explanatory variables should be reviewed for consideration of further engineering or elimination from usage.

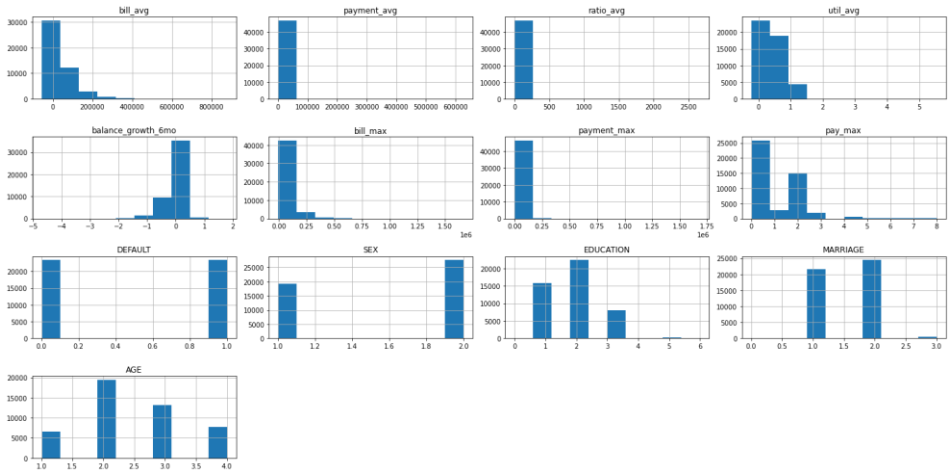


Figure 2: Binned Distribution of Variables

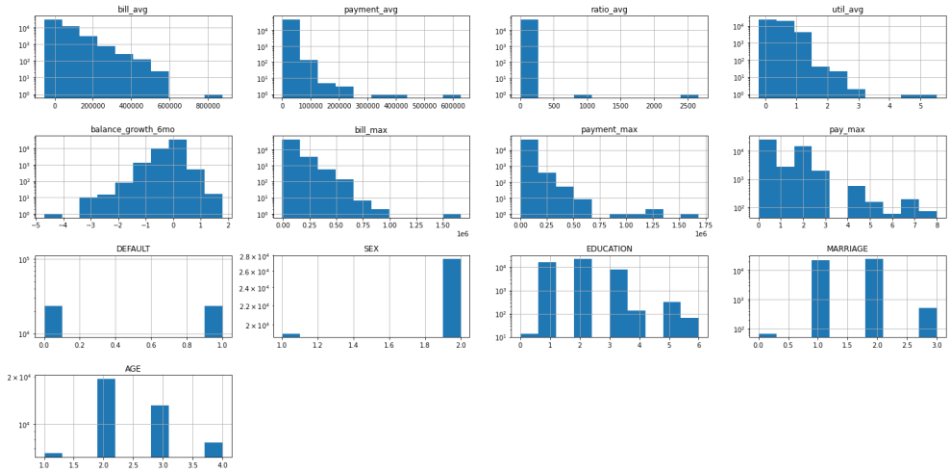


Figure 3: Binned Distribution of Variables – Log Transformed

A common practice for modeling data preparation is to log-transform the data in each variable to reduce skewness and achieve a more normal distribution (Feng et. al. 2014). Figure 3 shows how the transformation effects certain variables particularly in comparison with the original seen in Figure 2 – and is essential prior to using standardization or normalization across the set.

The target variable, DEFAULT, is found to be imbalanced, though not severely. This will require adjustment to accuracy measure and potentially modeling choices. Simple accuracy would not accurately call out a high false positive rate, while using F1 or confusion matrices as we plan to would help with representation.

Figure 4: Histogram of Target Variable

Rebalancing was tested by oversampling the positive default case (represented by "1").

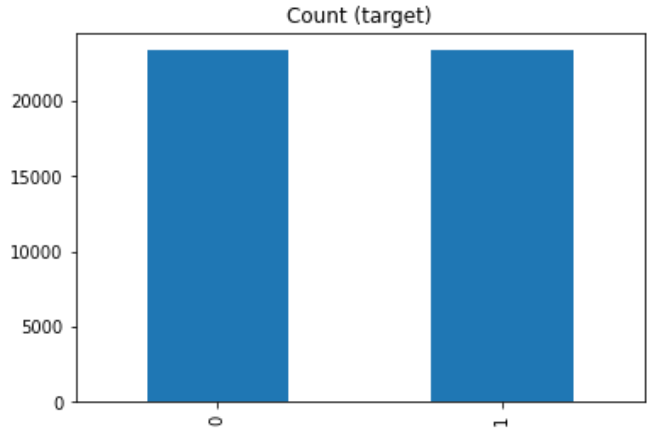


Figure 5: Re-sampled Target Variable Counts

The method used to calculate some of the engineered variables will require further adjustment. NAs result from 0 in the denominator (divide by 0 error) of division engineered variables. These fields must be filled in logically. Since a Pay Ratio is engineered by dividing the

payment each month by the previous month's balance, a balance of zero is a positive result and should be set to the maximum value for this field.

`pay_ratio1` has 2468 (8.2%) missing values	Missing
`pay_ratio2` has 2814 (9.4%) missing values	Missing
`pay_ratio3` has 3150 (10.5%) missing values	Missing
`pay_ratio4` has 3449 (11.5%) missing values	Missing
`pay_ratio5` has 3959 (13.2%) missing values	Missing
`ratio_avg` has 5791 (19.3%) missing values	Missing

Figure 6: Engineered Variable EDA Excerpt

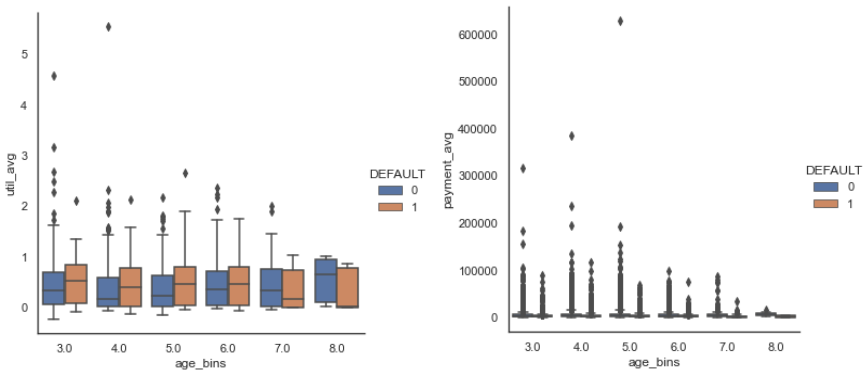


Figure 7: Payment and Utilization distribution over class by Age

Table 5: Data Quality Overview - Engineered

Column Name	Data Type	Present Values	Missing Values	Unique Values	Minimum Value	Maximum Value
DEFAULT	int32	30000	0	2	0	1
age_bins	category	30000	0	6	21-30	71-80
bill_avg	float64	30000	0	27370	-56043.166667	877313.833333
payment_avg	float64	30000	0	19180	0.0	627344.333333
pay_ratio1	float64	30000	0	20209	0.0	4444.333333
pay_ratio2	float64	30000	0	20042	0.0	5001.0
pay_ratio3	float64	30000	0	19411	0.0	4444.333333
pay_ratio4	float64	30000	0	18580	0.0	129.705128
pay_ratio5	float64	30000	0	18025	0.0	690.655172
ratio_avg	float64	30000	0	24820	0.0	2667.199955
util1	float64	30000	0	25565	-0.619892	6.4553
util2	float64	30000	0	25088	-1.39554	6.3805
util3	float64	30000	0	24738	-1.0251	10.688575
util4	float64	30000	0	24452	-1.3745	5.14685
util5	float64	30000	0	24075	-0.876743	4.9355
util6	float64	30000	0	24075	-0.876743	4.9355
util_avg	float64	30000	0	28402	-0.23259	5.537758
balance_growth_6mo	float64	30000	0	27137	-4.7004	1.7911
bill_max	int32	30000	0	23979	-6029	1664089
payment_max	int32	30000	0	11670	0	1684259
pay_max	float64	30000	0	9	0.0	8.0
DEFAULT	int32	30000	0	2	0	1

After cleaning the engineered variables, a review of the high level data quality report helps to determine if any further actions are necessary.

"Correlation allows you to interpret the covariance further by identifying both the direction and the strength of any association" (Tilman, 2016), and a correlation matrix makes this visually accessible across the range of explanatory variables and the target.

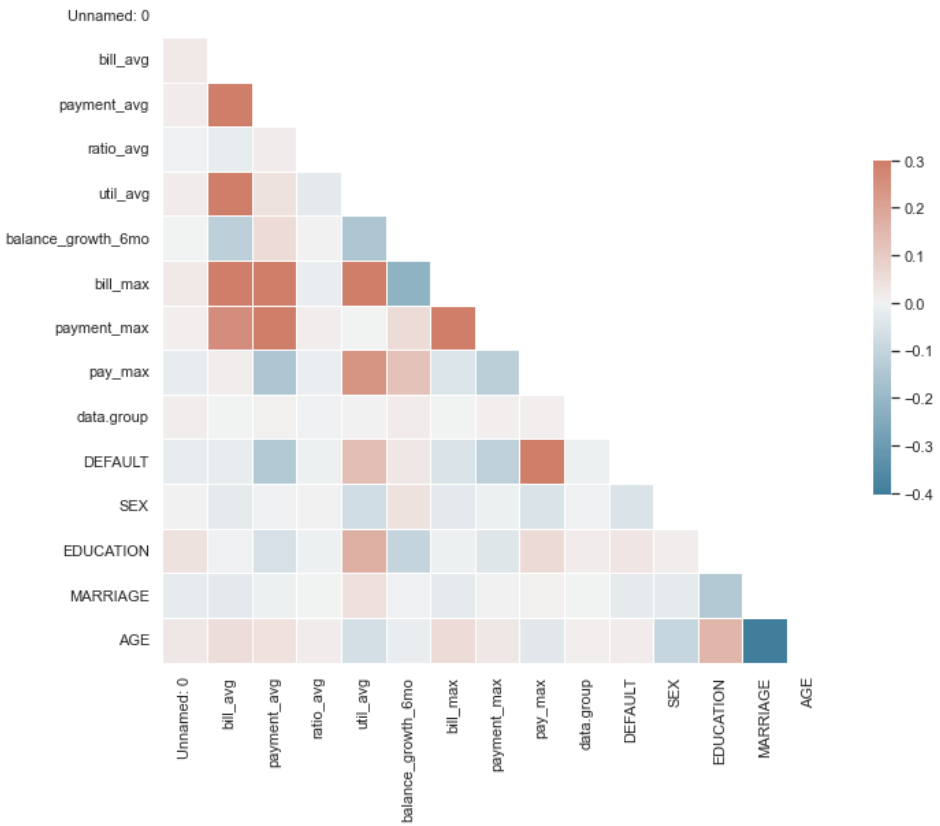


Figure 8: Correlation Plot of Target Variable and Engineered Variables

The matrix shows that several of the variables have very low coefficients with the target variable, “DEFAULT” and should be considered for dimension reduction. Explanatory variables that have high correlation with each other should also be considered for reduction (Gelman, 2014) as the intent of building a model is locating the variance or finding the signal in the noise. Multiple correlated signals does not contribute to the model; it is redundant & models perform better with fewer inputs.

The columns with the highest correlations (either negative or positive) with the target default are: payment_avg , util_avg , payment_max, and pay_max. payment_avg and payment_max are too highly correlated with each other to provide variance, and payment_max having the slightly lower correlation to the target means it should be eliminated. The boxplots display a lack of distinction of classes across two of the credit history-based variables, and some evidence of variance by age group though not drastic.

5. Predictive Modeling: Methods and Results

In addition to experimentation with data preparation and feature engineering, testing different model types and hyperparameters can yield vastly different prediction performance results. The model must be chosen based on the input data types and the priorities in performance. Although the data as it was provided has some time-series features, the intent of the problem statement is not a time-series problem. The fluctuations over time have been used to engineer features and we are not looking to predict "when" a consumer may default but "if".

a. Random Forest

The first model tested is random forest. Random forest models tend to perform well with few features and either categorical variables or binning implemented to allow each node in the constituent trees to have finite branches.

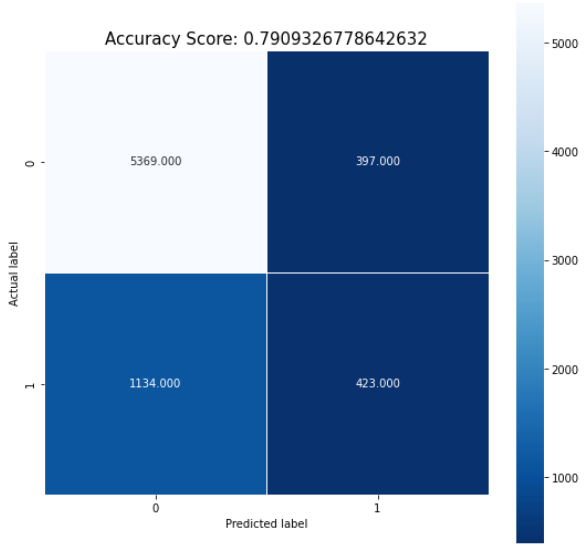


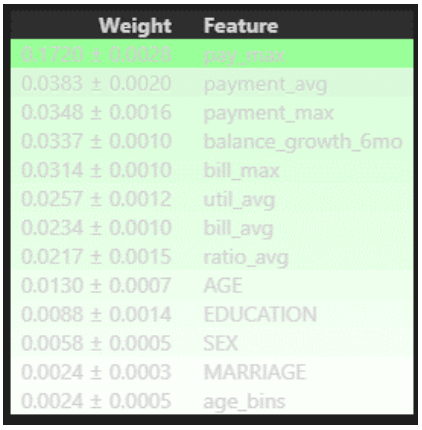
Figure 9: Confusion Matrix: Random Forest

Table 6: Classification Report: Random Forest

	Precision	Recall	F1-Score	Support
0	0.83	0.93	0.88	5766.00
1	0.52	0.27	0.36	1557.00
accuracy	0.79	0.79	0.79	0.79
macro avg	0.67	0.60	0.62	7323.00
weighted avg	0.76	0.79	0.76	7323.00

Random forest is a very flexible model that can be used across many domains and is a good general purpose tool. Right out of the box, performance is fairly good, though one area we will focus is the True Positive rate. Since the goal of this study is to predict when a customer will default, error here would likely be costly – with a borrower not paying back the money owed. A TPR of 27% is not sufficient for industry.

The variable performance plot is provided in Figure 7 and shows that by a factor of five pay_max is the most influential input variable.



Weight	Feature
0.1720 ± 0.0028	pay_max
0.0383 ± 0.0020	payment_avg
0.0348 ± 0.0016	payment_max
0.0337 ± 0.0010	balance_growth_6mo
0.0314 ± 0.0010	bill_max
0.0257 ± 0.0012	util_avg
0.0234 ± 0.0010	bill_avg
0.0217 ± 0.0015	ratio_avg
0.0130 ± 0.0007	AGE
0.0088 ± 0.0014	EDUCATION
0.0058 ± 0.0005	SEX
0.0024 ± 0.0003	MARRIAGE
0.0024 ± 0.0005	age_bins

Figure 10: Feature Importance: Random Forest

b. Gradient Boosting

The second model tested is XGBoost. XGBoost is similar to random forest in that it builds off decision trees. There are many difference though in how this is executed. While Random Forest uses hyperparameters to randomly generate many trees and develops an ensemble, XGboost uses the gradient to build one tree at a time and converge towards a solution by minimizing error (Chen, Tianqi, and Guestrin, 2016). XGBoost was able to produce higher accuracy and F1 score across the classes, making it a superior model to random forest in this case.

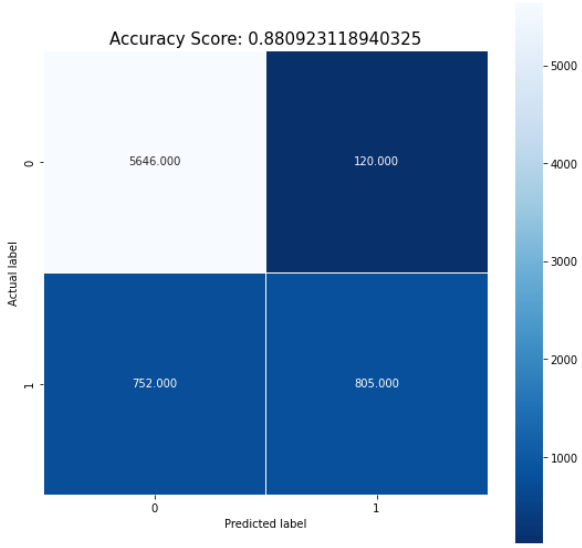


Figure 11: Confusion Matrix: XGBoost

Table 7: Classification Report: XGBoost

	Precision	Recall	F1-Score	Support
0	0.88	0.98	0.93	5766.00
1	0.87	0.52	0.65	1557.00
accuracy	0.88	0.88	0.88	0.88
macro avg	0.88	0.75	0.79	7323.00
weighted avg	0.88	0.88	0.87	7323.00

The variable performance plot is provided in Figure 9 and shows that by a factor of two pay_max is the most influential input variable. This agrees with random forest result, though the remaining variable order is different.

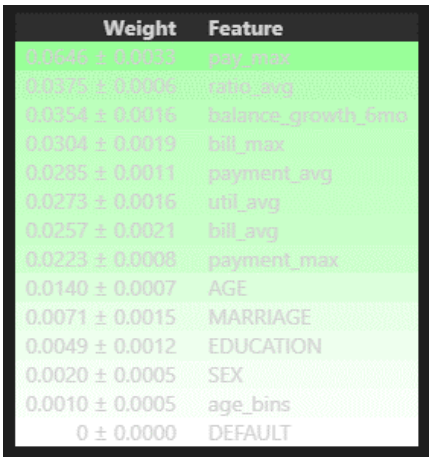


Figure 12: Feature Importance: XGBoost

c. Logistic Regression with Variable Selection

To develop a logistic regression model, the feature importance from the previous two models, Random Forest and XGboost, were used and the top three were taken from each. Logistic regression is one of the simplest data science approaches to fitting a model – simply using an algebraic expression with the number of variables chosen as a hyperparameter.

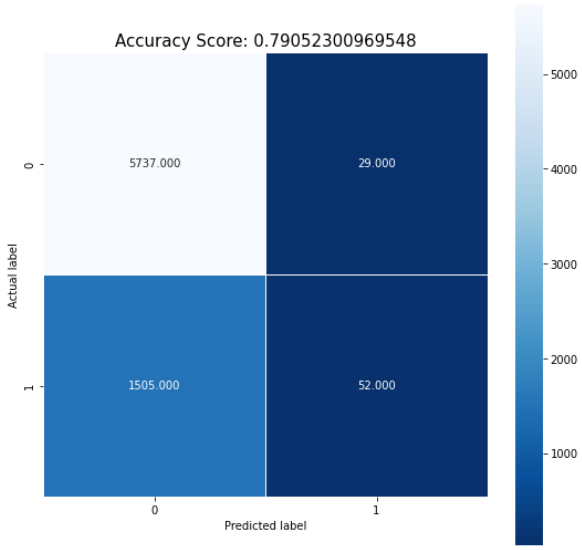


Figure 13: Confusion Matrix: Logistic Regression

Table 8: Classification Report: Logistic Regression

	Precision	Recall	F1-Score	Support
0	0.79	0.99	0.88	5766.00
1	0.64	0.03	0.06	1557.00
accuracy	0.79	0.79	0.79	0.79
macro avg	0.72	0.51	0.47	7323.00
weighted avg	0.76	0.79	0.71	7323.00

The results shown below are for a model using a second-degree equation.

Logit Regression Results

Dep. Variable:	y	No. Observations:	10000
Model:	Logit	Df Residuals:	9998
Method:	MLE	Df Model:	1
Date:	Sun, 14 Aug 2022	Pseudo R-squ.:	0.02248
Time:	18:50:40	Log-Likelihood:	-547.42
converged:	True	LL-Null:	-560.02
Covariance Type:	nonrobust	LLR p-value:	5.218e-07

	coef	std err	z	P>|z|	[0.025	0.975]
x1	6.5037	0.245	26.572	0.000	6.024	6.983
x2	-2.0074	0.107	-18.832	0.000	-2.216	-1.799

Figure 14: Variable and Result summary: Logistic Regression

d. Support Vector Machine

The support vector machine is implemented as a support vector classifier. SVMs can be thought similar to logistic regression, but instead of a single line to predict trends in the target variable, it uses geometry, potentially more complex, to split between the classes. Using a liner model to start makes sense since it the target class is binary.

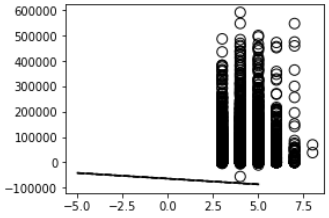


Figure 15: SVM Separating Hyperline – needs work

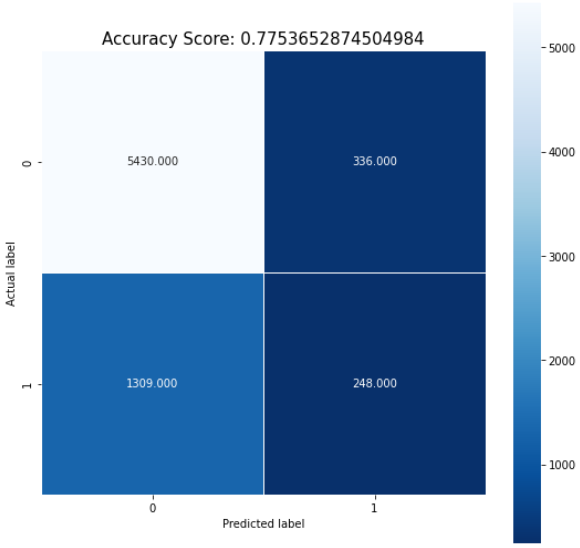


Figure 16: Confusion Matrix: SVM

Table 9: Classification Report: SVM

	Precision	Recall	F1-Score	Support
0	0.81	0.94	0.87	5766.00
1	0.42	0.16	0.23	1557.00
accuracy	0.78	0.78	0.78	0.78
macro avg	0.62	0.55	0.55	7323.00
weighted avg	0.72	0.78	0.73	7323.00

6. Comparison of Results

Throughout the initial models true negative rate is the highest class. False negatives are the common issue that is concerning, as failure to predict most of the defualting customers would be extremely costly for the company. False positives are the next concern, but less so as a lost customer is not as expensive as letting through a defaulting one. XGBoost is the best initial model that is able to deal with the target class imbalance.

After further feature engineering, balancing of the target variables, feature reductions, and hyperparameter optimization all of the models were able to be improved. A Recurrent Neural Network was also tested, but not further pursued and would be in a future study. Macro-averaged F1 score will be one measure to be focused on as it well represents both classes, and TPR would be important given the problem

Table 10: Model Results: Baseline

Model Type	Macro Avg	TPR
RF	0.62	0.27
XG	0.79	0.52
LR	0.79	0.03
SVM	0.55	0.16
RNN	0.66	0.59

Table 11: Model Results: Re-balanced

Model Type	Macro Avg	TPR
RF	0.65	0.42
XG	0.65	0.59
LR	0.46	0.89
SVM	0.47	0.81

Table 12: Model Results: Log-Scaled, Normalized

Model Type	Macro Avg	TPR
RF	0.65	0.42
XG	0.73	0.59
LR	0.73	0.67
SVM	0.49	0.78

7. Conclusions

The objective of credit risk modeling is to predict whether a customer will default on the money borrowed from an institution. If a firm relies on modeling that is unsuccessful, it cannot make profit and would thus not survive. In modern day credit industry, accurate models are required to remain competitive, and have allowed certain companies to lead. The models tested in this study produce a variety of outputs which could be chosen based on priority. A cost function would need to be considered before choosing a model, weighing costly false negatives against false positives that lose good customers. While logistic regression was able to achieve very high true positive rates, XGBoost generally performed better and with further feature engineering may yield the greatest profits.

8. Bibliography

1. Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

2. Yeh, I. C., and Lien, C. H. (2009). The comparisons of data mining techniques for the predictive accuracy of probability of default of credit card clients. Expert Systems with Applications, 36(2), 2473-2480.

3. Cagan, Michele. Debt 101: From Interest Rates and Credit Scores to Student Loans and Debt Payoff Strategies, an Essential Primer on Managing Debt. First Adams Media hardcover edition, Adams Media, 2020.

4. Dempsey, Robert. Python Business Intelligence Cookbook: Leverage the Computational Power of Python with More than 60 Recipes That Arm You with the Required Skills to Make Informed Business Decisions. 2015. Open WorldCat, https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1131993.

5. Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.3. https://CRAN.R-project.org/package=stargazer

6. Correa Bahnsen, Alejandro, et al. “Feature Engineering Strategies for Credit Card Fraud Detection.” *Expert Systems with Applications*, vol. 51, June 2016, pp. 134–42. *DOI.org (Crossref)*, https://doi.org/10.1016/j.eswa.2015.12.030.

7. L. Peng, W. Qing and G. Yujia, "Study on Comparison of Discretization Methods," 2009 International Conference on Artificial Intelligence and Computational Intelligence, 2009, pp. 380-384, doi: 10.1109/AICI.2009.385.

8. Waskom, Michael L. “Seaborn: Statistical Data Visualization.” Journal of Open Source Software, vol. 6, no. 60, 2021, p. 3021, https://doi.org/10.21105/joss.03021.

9. Gelman, Andrew. Bayesian Data Analysis. Third edition, CRC Press, 2014.

10. Feng C, Wang H, Lu N, Chen T, He H, Lu Y, Tu XM. Log-transformation and its implications for data analysis. Shanghai Arch Psychiatry. 2014 Apr;26(2):105-9. doi: 10.3969/j.issn.1002-0829.2014.02.009. Erratum in: Gen Psychiatr. 2019 Sep 6;32(5):e100146corr1. PMID: 25092958; PMCID: PMC4120293.

11. Chen, Tianqi, and Carlos Guestrin. “XGBoost: A Scalable Tree Boosting System.” Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, 2016, pp. 785–94. DOI.org (Crossref), https://doi.org/10.1145/2939672.2939785.

9. Appendix A: Data Dictionary

X1	LIMIT_BAL	Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.
X2	SEX	Gender (1 = male; 2 = female).
X3	EDUCATION	Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).
X4	MARRIAGE	Marital status (1 = married; 2 = single; 3 = others).
X5	AGE	Age (year).
History of monthly past payment. The measurement scale for the repayment status is: -1 = pay duly; 1 = payment delay for one month; 2 = payment delay for two months; . . .; 8 = payment delay for eight months; 9 = payment delay for nine months and above.		
X6	PAY_1	repayment status in September, 2005
X7	PAY_2	repayment status in August, 2005
X8	PAY_3	repayment status in July, 2005.
X9	PAY_4	repayment status in June, 2005.
X10	PAY_5	repayment status in May, 2005.
X11	PAY_6	repayment status in April, 2005.
Amount of bill statement (NT dollar)		
X12	BILL_AMT1	bill statement amount in September, 2005
X13	BILL_AMT2	bill statement amount in August, 2005
X14	BILL_AMT3	bill statement amount in July, 2005.
X15	BILL_AMT4	bill statement amount in June, 2005.
X16	BILL_AMT5	bill statement amount in May, 2005.
X17	BILL_AMT6	bill statement amount in April, 2005.

Amount of previous payment (NT dollar)		
X18	PAY_AMT1	amount paid in September, 2005
X19	PAY_AMT2	amount paid in August, 2005
X20	PAY_AMT3	amount paid in July, 2005.
X21	PAY_AMT4	amount paid in June, 2005.
X22	PAY_AMT5	amount paid in May, 2005.
X23	PAY_AMT6	amount paid in April, 2005.