Predicting consumer default on payment using data mining techniques

Data Mining Report

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Contents

Introduction

A large E-Commerce client is preparing to roll out a new consumer credit card, much like is common with competitors (Macy's, Amazon, Kroger, etc.). Besides encouraging customer loyalty, offering a consumer credit card also assists a company in offering promotions, collecting customer data, and making money from credit. As part of the preparation process, Group 4 Consultants has been tasked with developing predictive models to help this client evaluate credit card applications and quantify the risk associated with granting lines of credit to specific people. Determining risk is very important, because it will allow the company to determine whether or not to approve new lines of credit, and also the size of the credit limits. To this end, one of the highest priority models needs to accurately predict the likelihood that a credit applicant will make their next payment. This report will detail the work of Group 4 Consulting by introducing the sample data set, describing the modelling process, and recommending the best solutions.

System Design

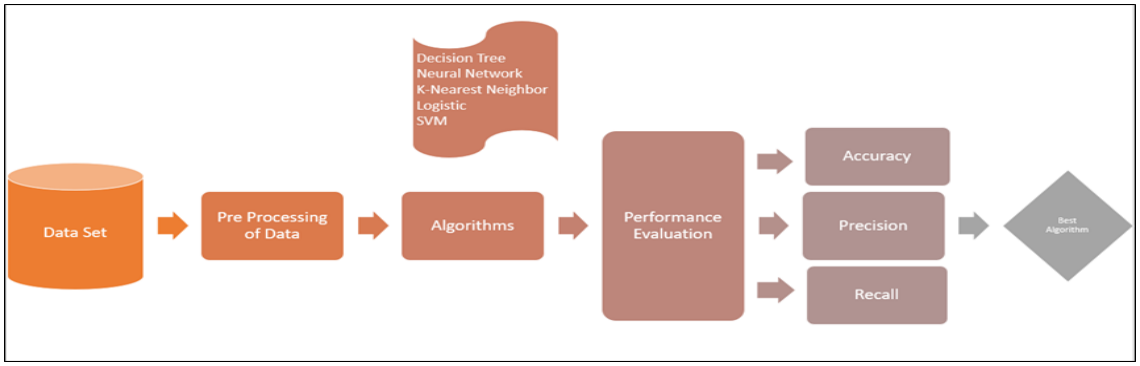


Figure 1: CRISP-DM Methodology

We have followed CRISP-DM Methodology in our Data mining process

Business Understanding

This initial phase focused on understanding the project objectives and requirements from a business perspective. Credit default has been a major challenge for our client as it endangers their system and pose chances of losses that might be hard to revert. Credit card defaulters are on the rise too. Our client wants to predict if a particular customer will default in his next month's payment. Based on the prediction our client will make necessary measures to tackle default customer as Credit risk will consumes capital and also eat into net profit margin (via loan loss provision expense)In order to create this predictive model, Group 4 Consulting used a data set that contained the credit card history and demographic data of 30,000 consumers in Taiwan (which is one of this E- Commerce company's primary markets). The set is called *Default of Credit Card Clients* and was found on the UCI Machine Learning Repository. This data initially contained 24 attributes, including demographic data (Gender, Education, Marital Status, Age) and credit history data (Credit Limit, Payment History, Bill Amount, Payment Amount). The fields of Payment History, Bill Amount, and Payment Amount all contained data for the past six months. For the purposes of this study, Bill Amount and Payment Amount were deemed redundant (much of the relevant information in these fields can be inferred by the Payment History field), so these fields were omitted. Below is a description of each field:

Variable Name	Type	Description
Limit Balance	Continuous	
Sex	Flag	Male Female
Education	Nominal	High School, University, Graduate School
Marriage	Categorical	Married, Single
Age	Nominal	
Pay (6 months)	Categorical	Revolving Credit Paid Duly Credit not used X Month Delay
Default	Categorical	Yes No

Figure 2 Data Description

Limit Balance can be understood as the total credit limit available to the applicant. Sex (Male/Female), Education (High School, College, Graduate School), Marriage (Single, Married), and Age are fairly self-explanatory. The Pay variable breaks down into the previous six months, and describes the payment history of the applicant. 'Revolving Credit' takes place when the applicant completely pays off their credit card bill. This applicant carries the least risk, but will not generate interest. 'Paid Duly' means that the applicant has been dutifully paying their credit card bills, but is not totally paying the credit line off. This can be a lucrative type of applicant from the perspective of the creditor, because they will accrue significant interest, but also pay their bills on time. 'Credit not used' simply happens when an applicant has not used their credit card in a given month and is not carrying a balance. Finally, 'X Month Delay' describes the riskiest type of applicant, and the variable X is the number of consecutive months that the applicant has missed their payments. The 'Default' field is the target variable that Group 4 Consulting is trying to develop predictive models for and is a Boolean value of whether or not the person paid the next bill.

Algorithms

Decision Tree

One of the most common, successful and transparent ways to do the required binary classification to “Yes” and “No” is via a Decision Tree. A tree structure is established with known facts and classifications in order to generalize relevant judgment rules. The decision trees used in this paper are CART, CHAID and C5.0 which are explained below.

CART (classification and regression tree) is a binary decision-tree technique. The Gini index aims to separate the largest category (measured by the number of observations) from others in the node. CHAID (chi-square automatic interaction detector) is a branch of the decision tree algorithm. e CHAID algorithm mainly relies on chi-square tests in the process of constructing decision trees, and the optimal splitting branch is identified by repeating the process of combinations and divisions. C5.0 was developed by Quinlan as an improvement of ID3. . The ID3 methodology refers to information gain as the criteria of constructing decision trees, and this typically results in over-learning due to an excessively large number of input variables. C5.0 uses the gains ratio to replace the previous criteria. However, the fundamental concept remains the same.

Table 1: Evaluation Summary

Measures	CHAID	CART	C5
Accuracy	79.24%	81.34%	81.66%
Sensitivity	35.77%	36.88%	32.30%
AUC	0.73	0.69	0.64
Specificity	92.02%	94.41%	96.17%

Artificial Neural Networks

Artificial neural networks can be a good solution for solving binary questions with very large data sets. In this case, our team is working with a data set of approximately 30,000 entries, and our

question is binary (will the applicant pay their next credit card bill, or not?). So, we attempt to model the problem with the following ANN methods:

- Multi-layer perceptron
- Radial basis function

Table 2: Summary of Results

	Overall Accuracy			Based on Validation Data	
Model	Training	Testing	Validation	Sensitivity	Specificity
Multi-Layer Perceptron MLP	81.69%	82.33%	81.10%	66.15%	94.78%
Radial Basis Function RBF	80.03%	80.66%	79.12%	63.54%	92.07%

In the chart above, the MLP produced stronger results than RBF in most categories. It produced a slightly higher accuracy in each partition, and a significantly higher sensitivity and specificity. Since the training and validation data accuracy percentages are close in both models, overfitting was not an issue here. Neither of the methods had an issue with perpetual training either, and both models finished running in under 1 minute. Regardless of this, MLP is recommended as the reference model for Artificial Neural Network.

Predictor Importance

In the MLP, the strongest predictor of the target variable was the field PAY_REVOLVING_CREDIT, which represents the most recent month's payment history. The second strongest predictor was LIMIT_BAL, which is the credit limit of the applicant. Both fields totally make sense from a logical and contextual perspective as well, so they probably have value in a business context. After that, the predictor importance plateaus amongst several determinants, so any other inferences wouldn't be very valuable:

ANN Recommendation

This model seemed to excel at predicting certain outcomes and fail at others. The confusion matrix below will help to elaborate:

Table 3: ANN Classification Table

Observed	Predicted	
	No	Yes
No	95.7%	4.3%
Yes	67.3%	32.7%

This matrix is taken from all aggregated partitions of the MLP model. As can be seen, the model is extremely successful at accurately predicting 'No', which means that the applicant will not pay the next month's credit card bill. The model will almost never predict 'Yes' when the result is 'No' (hence the very high specificity). However, the model fails miserably at predicting 'Yes' outcomes. Approximately 2/3 of the time, the model will be wrong when the outcome is 'Yes'. From a contextual standpoint, this means that the model will be very selective in predicting who will pay their next bill. If the business wants to be conservative and only grant credit to applicants who will almost surely make their payments, the MLP ANN could be a good model to use to help make decisions. But, if the company wants to liberally grant credit to more applicants, even if they might not pay the bill, this would be a poor model choice.

Support Vector Machine:

Since we want to predict whether a potential customer will default on their next payment or not, it is a binary classification problem. Therefore, SVM can be a great algorithm to solve this problem. We will run following kernels for SVM algorithm:

1) Radial Basis Function (RBF)
2) Polynomial
3) Sigmoid
4) Linear

Table 4: Summary of Results:

	Overall Accuracy			Based on Validation Data	
Model	Training	Testing	Validation	Sensitivity	Specificity
RBF (c=1, RBF Gamma =0.25)	84.65%	82.55%	81.32%	34.52%	95.09%
RBF (c=10, RBF Gamma =0.5)	92.54%	79.16%	77.47%	37.10%	89.35%
RBF (c=3, RBF Gamma =0.3)	90.76%	80.58%	78.93%	38.95%	90.70%
RBF (c=2, RBF Gamma =0.4)	91.01%	80.61%	79.22%	38.88%	91.09%
Polynomial	-	-	-	-	-
Linear	81.79%	82.42%	81.61%	32.15%	96.15%
Sigmoid	77.80%	77.78%	77.27%	-	-
Sigmoid	77.80%	77.78%	77.27%	-	-

RBF:

RBF function has various settings with which we will play to tune the model

Settings:

Since we have 12 variables in our dataset, the recommended value for RBF gamma is 3/12 to 6/12 which is from 0.25 to 0.5. Another parameter is C also called as regularization parameter; the recommended value is between 1 and 10. We will start with the minimum value of C as higher values can lead to overfitting problem.

RBF (First Run)

We ran RBF model with minimum settings i.e. c=1, RBF gamma=0.25. After running we got the results that are shown in summary results. We can see that the overfitting is rather less as the difference between training and validation results is minimal. The specificity (detection of default) is outstanding. On the other hand, sensitivity, the detection of customers who will not default on the next payment is rather poor. Which warrants for tuning the model

RBF (Second Run)

This time we ran the model with maximum setting i.e. c=10 and RBF gamma=0.5. These settings give the worst result. Overfitting is very high as can be seen in the summary results. Moreover, specificity drops down to 89 from 95. May be we need to have midrange settings.

RBF (Third run)

In this iteration, we have c=3 and RBF gamma is 0.30. After running these settings, the results are not much different.

RBF (Fourth run)

We further tuned the model with c=2 and RBF gamma to 0.4. Performance improved only a tiny bit but the overfitting is still very high. It seems that RBF gamma value higher than 0.25 drastically reduces prediction power of our model.

Dropping variables:

We tried to drop some variables such as age to see how it impacts our model. The results showed that it did not make any significant difference. Therefore, due to limitations of time and scope we will not tune the model any further.

In conclusion, RBF with C=1 and RBF gamma =0.25 gives us the best result.

Polynomial and Sigmoid:

For our dataset, polynomial and sigmoid functions did not perform at all. The polynomial function ran for more than 12 hours and still did not produce any results so we concluded that it is not relevant for our dataset and the question we are trying to answer.

Similarly, sigmoid function did not give complete confusion matrix when we ran it. It did not indicate any TP values which indicates that it is also not the best model for our dataset.

Linear Function:

Surprisingly, despite being the simplest kernel, linear kernel gives us the best result. The overfitting is minimal, and the specificity is higher than RBF.

SVM Conclusion:

We prefer linear kernel as it is simpler than RBF and provides superior results.

K-Nearest Neighbor

KNN has its own advantage when dealing with large dataset since KNN uses lazy learning which leads less computational power and time. However, finding the optimal k value take some effort. In order to calculate the k value for "Default Credit Card Client" dataset, 10% of sample data was ran against KNN algorithm and let the model to choose k value between 3 to 12. Selecting sex, age, education and Marital status from the feature selection gave the best k which is 8. (See Appendix A Figure 1,2 & 3)

After finding the optimal k the model was ran against the actual data which was partitioned into training, validation and testing, generating overall accuracy of 82.78%, 82.05% and 83.10% respectively. (See Appendix A Figure 4)

Table 5: Classification Table

Observed	Predicted	
	Not Default	Default
Not Default	4471	179
Default	937	388

Table 6: KNN Evaluation Summary

Model	Accuracy	Precision	Recall	Specificity	F1
KNN	81.32%	82.67%	96.15%	29.28%	88.90%

KNN recommendation

- high recall means that an algorithm returned most of the relevant results
- Using a test with **poor specificity** will result in a customer appearing to be a default customer, when he is, in fact, not default which may result losing some good customers

Logistic Regression:

Logistic regression is an efficient and powerful way to analyze the effect of a group of independent variables on a binary outcome by quantifying each independent variable unique contribution. Using components of linear regression reflected in the logit scale, logistic regression iteratively identifies the strongest linear combination of variables with the greatest probability of detecting the observed outcome.

Assumptions:

- We have one or more independent variables, which can be either continuous (i.e., an interval or ratio variable) or categorical (i.e., an ordinal or nominal variable)
- There needs to be a linear relationship between any continuous independent variables and the logit transformation of the dependent variable
- We should have independence of observations and the dependent variable should have mutually exclusive and exhaustive categories

One of the most common, successful and transparent ways to do the required binary classification to "good" and "bad" is via a logistic function. This is a function that takes as input the client characteristics and outputs the probability of default.

$$p = \frac{\exp(\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n)}{1 + \exp(\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n)}$$

where in the above

- p is the probability of default
- x_i is the explanatory factor i
- β_i is the regression coefficient of the explanatory factor i
- n is the number of explanatory variables

For each of the existing data points it is known whether the client has gone into default or not (i.e. p=1 or p=0). The aim in the here is to find the coefficients β0,…, βn such that the model's probability of default equals to the observed probability of default. Typically, this is done through

maximum likelihood. In reality, default probability will depend on the client characteristics in a more complicated way.

Model Performance:

As shown in fig 5, the evaluation metrics of all training, testing and validation datasets are provided. We are choosing validation dataset results which is tuned.

Accuracy is 82.66% with Area Under the curve is 0.714

Goodness of Fit:

- A statistically significant result (i.e., $p < .05$) indicates that the model does not fit the data well. You can see from the table above that the p-value is 0.259 (i.e., $p = 0.259$) therefore, not statistically significant. "Pearson", presents the Pearson chi-square statistic.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1604.896	1569	.259
Deviance	1336.045	1569	1.000

Pseudo R-Square

Cox and Snell	.244
Nagelkerke	.370
McFadden	.260

- Large chi-square values indicate a poor fit for the model.
- Based on this measure, the model fits the data well.
- In multinomial logistic regression you can also consider measures that are similar to R^2 in ordinary least-squares linear regression, which is the proportion of variance that can be explained by the model.

Accuracy	82.66%
Sensitivity	36.00%
Specificity	95.32%
AUC	0.714

We found out that the above-mentioned measurements from Logistic Regression. We also observed that the revolving credit had the most importance (fig: 6)

Final Recommendation

After comparing the performance of all the models, we had quite similar results for SVM, and decision tree. However, we prefer and recommend C5-decision tree algorithm over SVM. The simple reason for doing so is that we can dig deep into the decision trees and see if the rules generated by algorithm make real business sense or not. In contrast, SVM does not provide any visibility on how it reached to the solution therefore we cannot analyze if the output really makes business sense or not.

While analyzing C5, we found that it had great specificity i.e. detecting default on next payment with over 96.01% success rate based on testing data and 35.09% detection rate of customers who will not default on their next payment. The most influential variable in detecting default was revolving credit and this makes sense because paying minimum amount causes deep to increase gradually, making it likely for customer to default on the next payment. We can, with certain confidence, recommend our model since it will perform well in detecting default.

Challenges

The dataset we obtained was quite large and complex and required a lot of cleaning. We did not have enough time and scope to tune our models to perfection or to go back and re-prepare data for finer results. We, however, provided our best estimate for detecting customer default. We

also had huge problems with some of the kernels of SVM such as polynomial that ran for hours and did not produce any results and sigmoid that did not give complete results even though we tried dropping some variables.

Next Steps

To take this forward, we would like to spend more time on understanding the business and ask more relevant and specific business questions. In addition, we would like to spend more time on cleaning our data for better results. This will require considerable amount of time on tuning and going back to the data for adjustment. We would also like to come up with a schedule to re-train our model to keep it up to date with the latest data so that it can continue to detect fraud accurately.

Conclusion

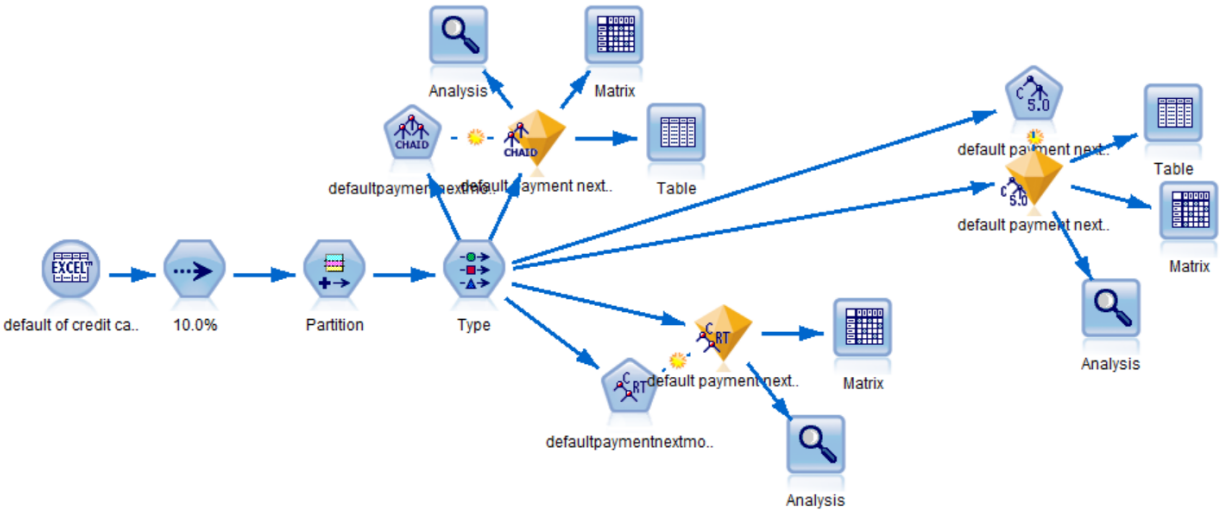
Our client, a large online retailer, wants to extend it line of credit to customers to increase its sales and convenience for customers. However, to mitigate the risk of default on payments, they want a reliable model to predict the potential customers who will default on their next payments. We, Group 4, accessed, cleaned and prepared the financial data for analysis. We analyzed 12 variables such as age, credit limit, payment history, marital status, etc and ran the data through five machine learning algorithms namely, decision trees, artificial neural networks, support

vector machine, k-nearest neighbors, and logistic regression to predict the default on next payment.

After careful analysis, we recommend C5 decision tree algorithm to detect potential default on next payment. C5 is better as it provides us visibility to the rules it generates, and we can analyze decision tree by digging deep into it if it makes any real-world sense. Moreover, C5's specificity and sensitivity were one of the highest among other ML algorithms we tested. According to our analysis, C5 can predict potentially defaulting customers with more than 96% success and the customers who will not default with the success of 35%. Since our model performs fairly well in detecting fraud, we can confidently recommend it. Finally, we will continue to work on perfecting our model and address the challenges and follow the next steps we have mentioned in our report.

Appendix A

Decision Tree



C5:

Results for output field default payment next month

Individual Models

Comparing $C-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	1,376	81.86%	508	83.83%	494	81.12%
Wrong	305	18.14%	98	16.17%	115	18.88%
Total	1,681		606		609	

Coincidence Matrix for $C-default payment next month (rows show actuals)

'Partition' = 1_Training	No	Yes
No	1,260	37
Yes	268	116

'Partition' = 2_Testing	No	Yes
No	466	16
Yes	82	42

'Partition' = 3_Validation	No	Yes
No	454	18
Yes	97	40

Performance Evaluation

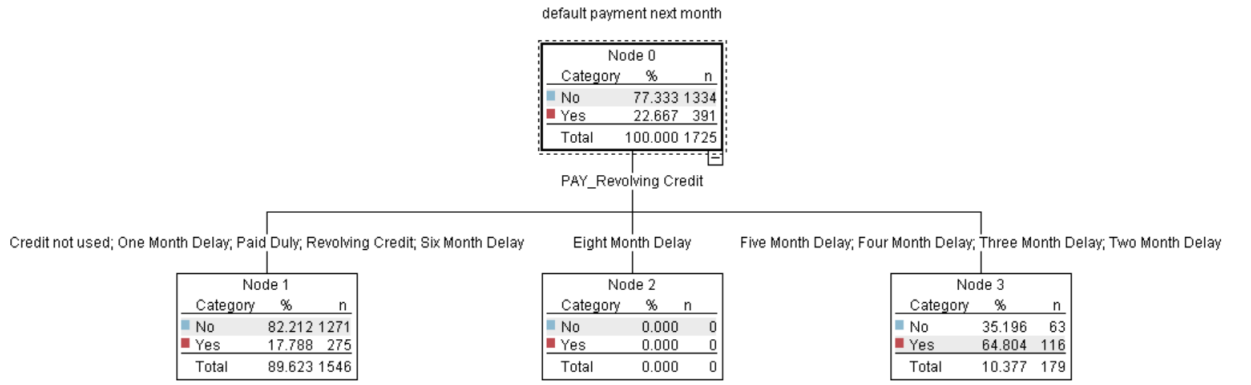
'Partition' = 1_Training	
No	0.066
Yes	1.2

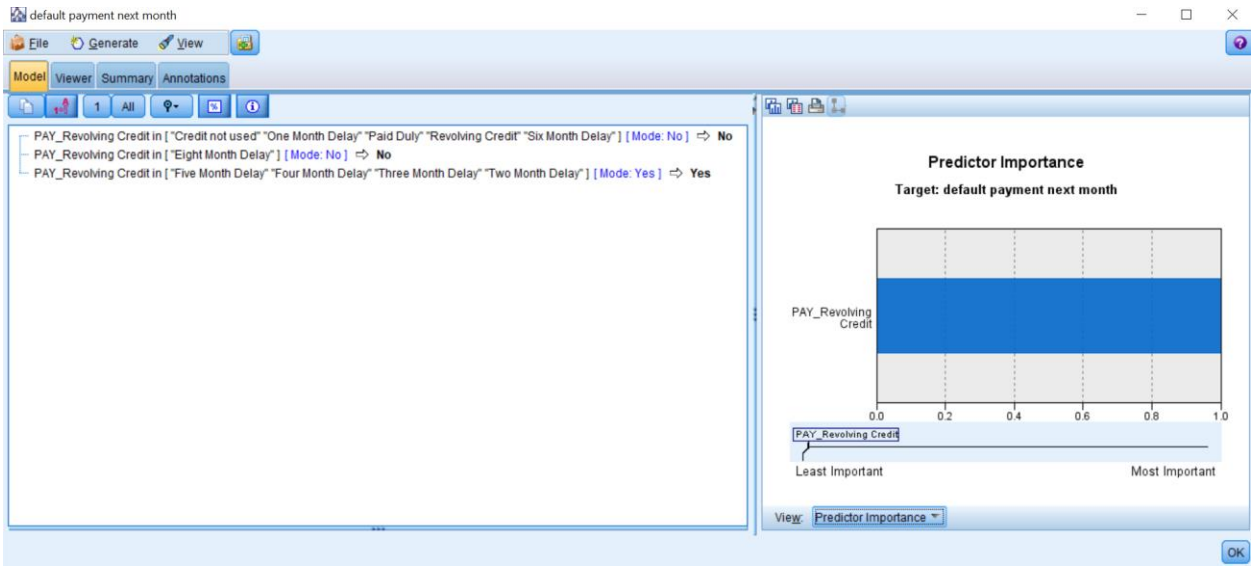
'Partition' = 2_Testing	
No	0.067
Yes	1.264

'Partition' = 3_Validation	
No	0.061
Yes	1.12

Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$C-default payment next month	0.639	0.279	0.653	0.306	0.63	0.261





CART:

Results for output field default payment next month

Individual Models

Comparing $R-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	1,352	80.67%	502	82.84%	493	81.35%
Wrong	324	19.33%	104	17.16%	113	18.65%
Total	1,676		606		606	

Coincidence Matrix for $R-default payment next month (rows show actuals)

'Partition' = 1_Training	No	Yes
No	1,204	82
Yes	242	148

'Partition' = 2_Testing	No	Yes
No	450	28
Yes	76	52

'Partition' = 3_Validation	No	Yes
No	447	24
Yes	89	46

Performance Evaluation

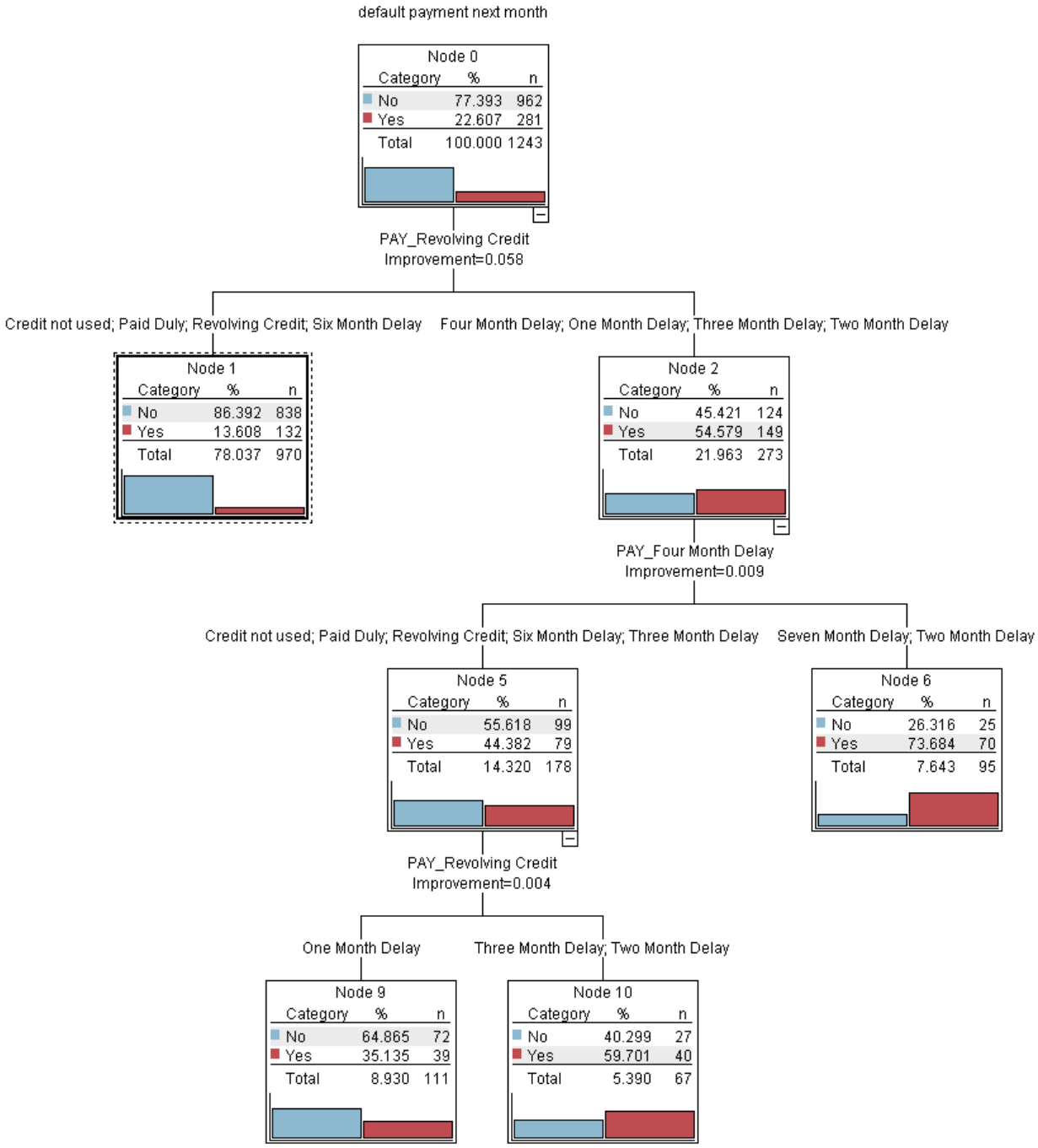
'Partition' = 1_Training	
No	0.082
Yes	1.017

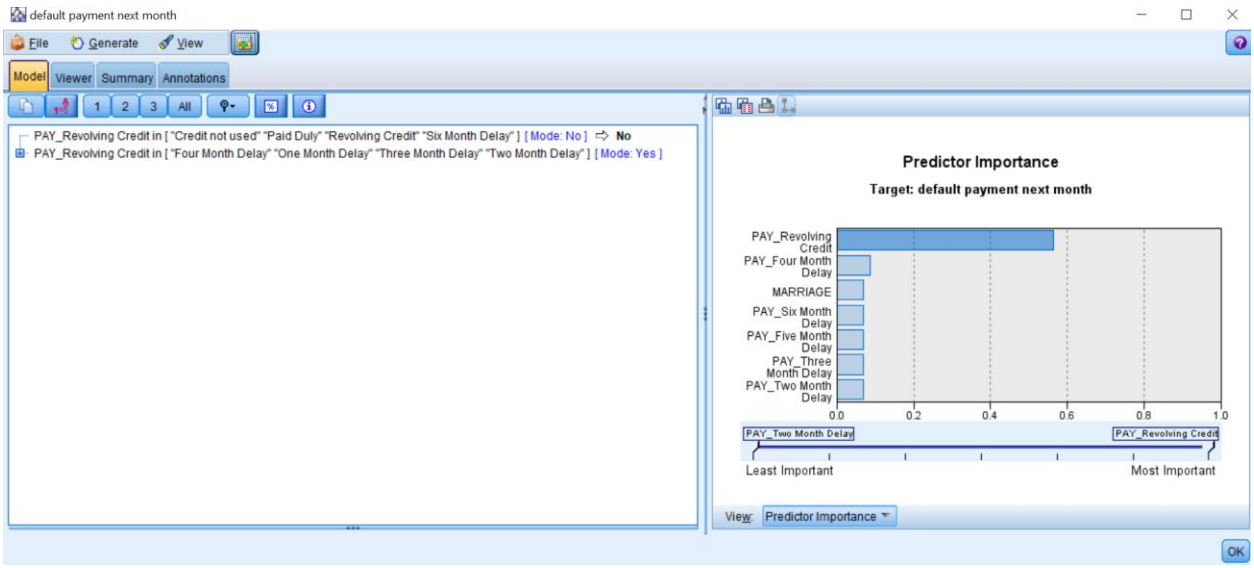
'Partition' = 2_Testing	
No	0.081
Yes	1.124

'Partition' = 3_Validation	
No	0.07
Yes	1.082

Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$R-default payment next month	0.675	0.35	0.699	0.398	0.694	0.389


default payment next month
Node 0
Category % n
No 77.393 962
Yes 22.607 281
Total 100.000 1243
PAY_Revolving Credit
Improvement=0.058
Credit not used; Paid Duly; Revolving Credit; Six Month Delay
Four Month Delay; One Month Delay; Three Month Delay; Two Month Delay
Node 1
Category % n
No 86.392 838
Yes 13.608 132
Total 78.037 970
Node 2
Category % n
No 45.421 124
Yes 54.579 149
Total 21.963 273
PAY_Four Month Delay
Improvement=0.009
Credit not used; Paid Duly; Revolving Credit; Six Month Delay; Three Month Delay
Seven Month Delay; Two Month Delay
Node 5
Category % n
No 55.618 99
Yes 44.382 79
Total 14.320 178
Node 6
Category % n
No 26.316 25
Yes 73.684 70
Total 7.643 95
PAY_Revolving Credit
Improvement=0.004
One Month Delay
Three Month Delay; Two Month Delay
Node 9
Category % n
No 64.865 72
Yes 35.135 39
Total 8.930 111
Node 10
Category % n
No 40.299 27
Yes 59.701 40
Total 5.390 67



CHAID:

Results for output field default payment next month

Individual Models

Comparing $R-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	1,367	79.62%	502	80.58%	499	80.61%
Wrong	350	20.38%	121	19.42%	120	19.39%
Total	1,717		623		619	

Coincidence Matrix for $R-default payment next month (rows show actuals)

'Partition' = 1_Training	No	Yes
No	1,223	119
Yes	231	144

'Partition' = 2_Testing	No	Yes
No	438	36
Yes	85	64

'Partition' = 3_Validation	No	Yes
No	451	38
Yes	82	48

Performance Evaluation

'Partition' = 1_Training	
No	0.073
Yes	0.919

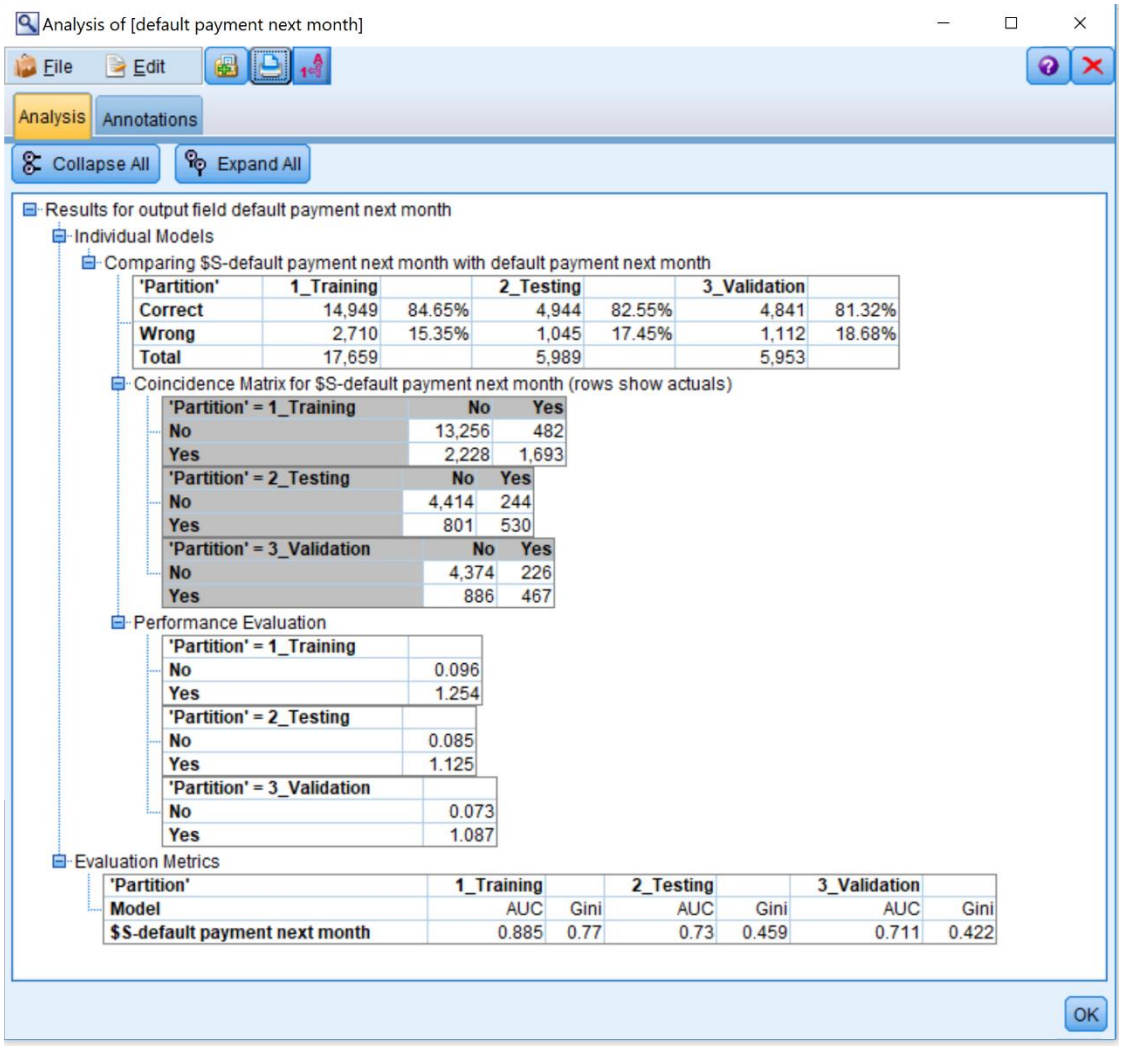
'Partition' = 2_Testing	
No	0.096
Yes	0.984

'Partition' = 3_Validation	
No	0.069
Yes	0.977

Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$R-default payment next month	0.726	0.452	0.794	0.588	0.705	0.411

RBF 1



'Partition'	1_Training		2_Testing		3_Validation	
Correct	14,949	84.65%	4,944	82.55%	4,841	81.32%
Wrong	2,710	15.35%	1,045	17.45%	1,112	18.68%
Total	17,659		5,989		5,953	

'Partition' = 1_Training	No	Yes
No	13,256	482
Yes	2,228	1,693

'Partition' = 2_Testing	No	Yes
No	4,414	244
Yes	801	530

'Partition' = 3_Validation	No	Yes
No	4,374	226
Yes	886	467

'Partition' = 1_Training	
No	0.096
Yes	1.254

'Partition' = 2_Testing	
No	0.085
Yes	1.125

'Partition' = 3_Validation	
No	0.073
Yes	1.087

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$S-default payment next month	0.885	0.77	0.73	0.459	0.711	0.422

RBF-2

- Analysis
  - Analysis of default of credit card clients_cleaned.xls (Apr 17, 2018 11:44:26 PM)
- Fields
- Build Settings
  - Use partitioned data: true
  - Partition: Partition
  - Calculate predictor importance: true
  - Calculate raw propensity scores: false
  - Calculate adjusted propensity scores: false
  - Mode: Expert
  - Append all probabilities (valid only for categorical targets): true
  - Stopping criteria: 1.0E-3
  - Kernel type: RBF
  - Regularization parameter : 10
  - Regression precision (epsilon): 0.1
  - RBF gamma: 0.5
  - Gamma: 1.0
  - Bias: 0.0
  - Degree: 3
- Training Summary

- Results for output field default payment next month
  - Individual Models
    - Comparing $S-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	16,342	92.54%	4,741	79.16%	4,612	77.47%
Wrong	1,317	7.46%	1,248	20.84%	1,341	22.53%
Total	17,659		5,989		5,953	

    - Coincidence Matrix for $S-default payment next month (rows show actuals)

'Partition' = 1_Training	No	Yes
No	13,548	190
Yes	1,127	2,794

'Partition' = 2_Testing	No	Yes
No	4,170	488
Yes	760	571

'Partition' = 3_Validation	No	Yes
No	4,110	490
Yes	851	502

    - Performance Evaluation

'Partition' = 1_Training	
No	0.171
Yes	1.439

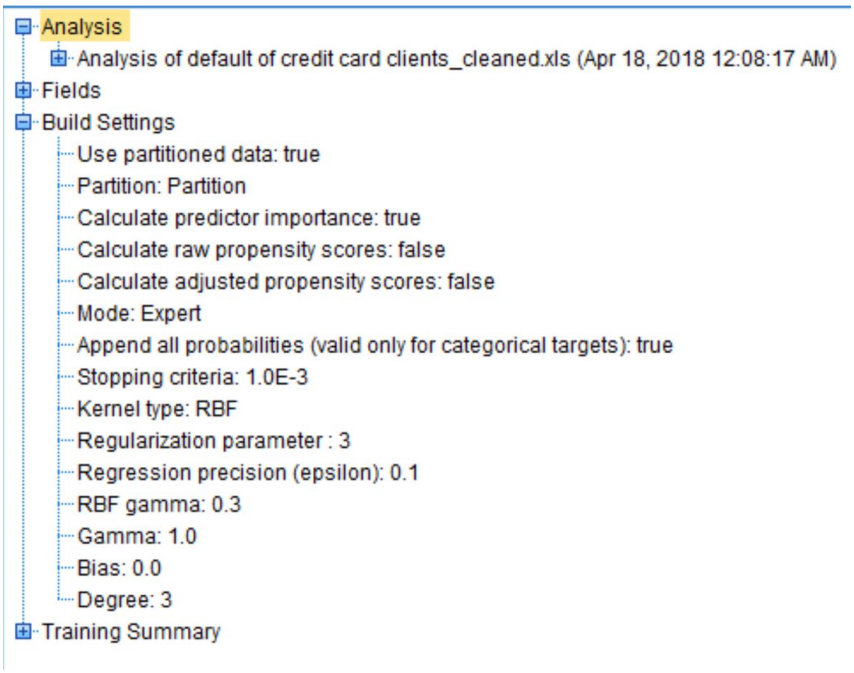
'Partition' = 2_Testing	
No	0.084
Yes	0.886

'Partition' = 3_Validation	
No	0.07
Yes	0.8

  - Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$S-default payment next month	0.924	0.847	0.71	0.42	0.695	0.39

RBF-3



Results for output field default payment next month

Individual Models

Comparing $S-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	16,028	90.76%	4,826	80.58%	4,699	78.93%
Wrong	1,631	9.24%	1,163	19.42%	1,254	21.07%
Total	17,659		5,989		5,953	

Coincidence Matrix for $S-default payment next month (rows show actuals)

'Partition' = 1_Training	No	Yes
No	13,444	294
Yes	1,337	2,584

'Partition' = 2_Testing	No	Yes
No	4,238	420
Yes	743	588

'Partition' = 3_Validation	No	Yes
No	4,172	428
Yes	826	527

Performance Evaluation

'Partition' = 1_Training	
No	0.156
Yes	1.397

'Partition' = 2_Testing	
No	0.09
Yes	0.965

'Partition' = 3_Validation	
No	0.077
Yes	0.887

Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$S-default payment next month	0.909	0.818	0.72	0.44	0.702	0.404

RBF-4

- Analysis
  - Analysis of default of credit card clients_cleaned.xls (Apr 18, 2018 12:14:15 AM)
- Fields
- Build Settings
  - Use partitioned data: true
  - Partition: Partition
  - Calculate predictor importance: true
  - Calculate raw propensity scores: false
  - Calculate adjusted propensity scores: false
  - Mode: Expert
  - Append all probabilities (valid only for categorical targets): true
  - Stopping criteria: 1.0E-3
  - Kernel type: RBF
  - Regularization parameter : 2
  - Regression precision (epsilon): 0.1
  - RBF gamma: 0.4
  - Gamma: 1.0
  - Bias: 0.0
  - Degree: 3
- Training Summary

- Results for output field default payment next month
  - Individual Models
    - Comparing $S-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	16,072	91.01%	4,828	80.61%	4,716	79.22%
Wrong	1,587	8.99%	1,161	19.39%	1,237	20.78%
Total	17,659		5,989		5,953	

    - Coincidence Matrix for $S-default payment next month (rows show actuals)

'Partition' = 1_Training	No	Yes
No	13,450	288
Yes	1,299	2,622

'Partition' = 2_Testing	No	Yes
No	4,240	418
Yes	743	588

'Partition' = 3_Validation	No	Yes
No	4,190	410
Yes	827	526

    - Performance Evaluation

'Partition' = 1_Training	
No	0.159
Yes	1.401

'Partition' = 2_Testing	
No	0.09
Yes	0.967

'Partition' = 3_Validation	
No	0.078
Yes	0.905

  - Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$S-default payment next month	0.909	0.817	0.727	0.454	0.707	0.415

Sigmoid-1

- Analysis
  - Analysis of default of credit card clients_cleaned.xls (Apr 18, 2018 11:37:45 PM)
  - Analysis of default of credit card clients_cleaned.xls (Apr 18, 2018 11:39:16 PM)
- Fields
- Build Settings
  - Use partitioned data: true
  - Partition: Partition
  - Calculate predictor importance: false
  - Calculate raw propensity scores: false
  - Calculate adjusted propensity scores: false
  - Mode: Expert
  - Append all probabilities (valid only for categorical targets): false
  - Stopping criteria: 1.0E-3
  - Kernel type: Sigmoid
  - Regularization parameter : 10
  - Regression precision (epsilon): 0.1
  - RBF gamma: 0.1
  - Gamma: 2.0
  - Bias: 0.0
  - Degree: 3
- Training Summary

- Results for output field default payment next month
  - Individual Models
    - Comparing $S-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	13,738	77.8%	4,658	77.78%	4,600	77.27%
Wrong	3,921	22.2%	1,331	22.22%	1,353	22.73%
Total	17,659		5,989		5,953	

    - Coincidence Matrix for $S-default payment next month (rows show actuals)

'Partition' = 1_Training	No
No	13,738
Yes	3,921

'Partition' = 2_Testing	No
No	4,658
Yes	1,331

'Partition' = 3_Validation	No
No	4,600
Yes	1,353

    - Performance Evaluation

'Partition' = 1_Training	
No	0.0

'Partition' = 2_Testing	
No	0.0

'Partition' = 3_Validation	
No	0.0

  - Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$S-default payment next month	0.52	0.041	0.517	0.034	0.52	0.041

Sigmoid-2

- Analysis
  - Analysis of default of credit card clients_cleaned.xls (Apr 19, 2018 12:54:13 AM)
- Fields
- Build Settings
  - Use partitioned data: true
  - Partition: Partition
  - Calculate predictor importance: false
  - Calculate raw propensity scores: false
  - Calculate adjusted propensity scores: false
  - Mode: Expert
  - Append all probabilities (valid only for categorical targets): false
  - Stopping criteria: 1.0E-3
  - Kernel type: Sigmoid
  - Regularization parameter : 10
  - Regression precision (epsilon): 0.1
  - RBF gamma: 0.1
  - Gamma: 3.0
  - Bias: 0.0
  - Degree: 3
- Training Summary

- Results for output field default payment next month
  - Individual Models
    - Comparing $S-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	13,738	77.8%	4,658	77.78%	4,600	77.27%
Wrong	3,921	22.2%	1,331	22.22%	1,353	22.73%
Total	17,659		5,989		5,953	

    - Coincidence Matrix for $S-default payment next month (rows show actuals)

'Partition' = 1_Training	No
No	13,738
Yes	3,921

'Partition' = 2_Testing	No
No	4,658
Yes	1,331

'Partition' = 3_Validation	No
No	4,600
Yes	1,353

    - Performance Evaluation

'Partition' = 1_Training	
No	0.0

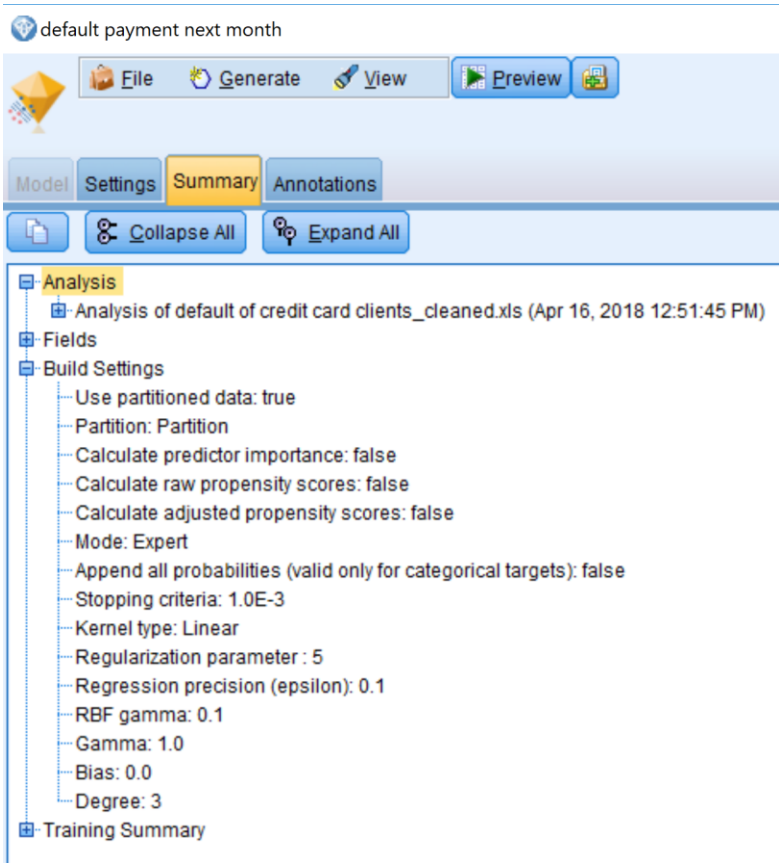
'Partition' = 2_Testing	
No	0.0

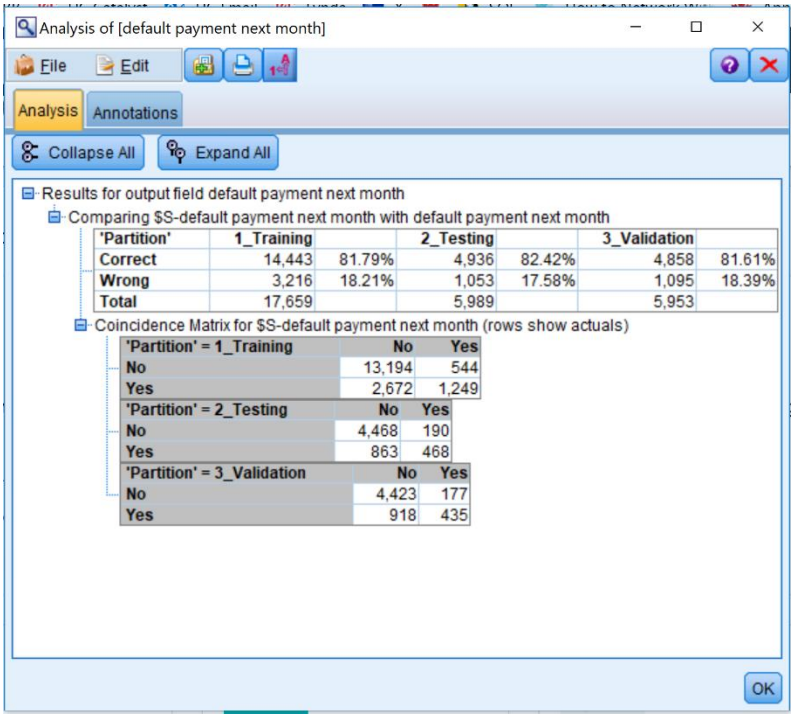
'Partition' = 3_Validation	
No	0.0

  - Evaluation Metrics

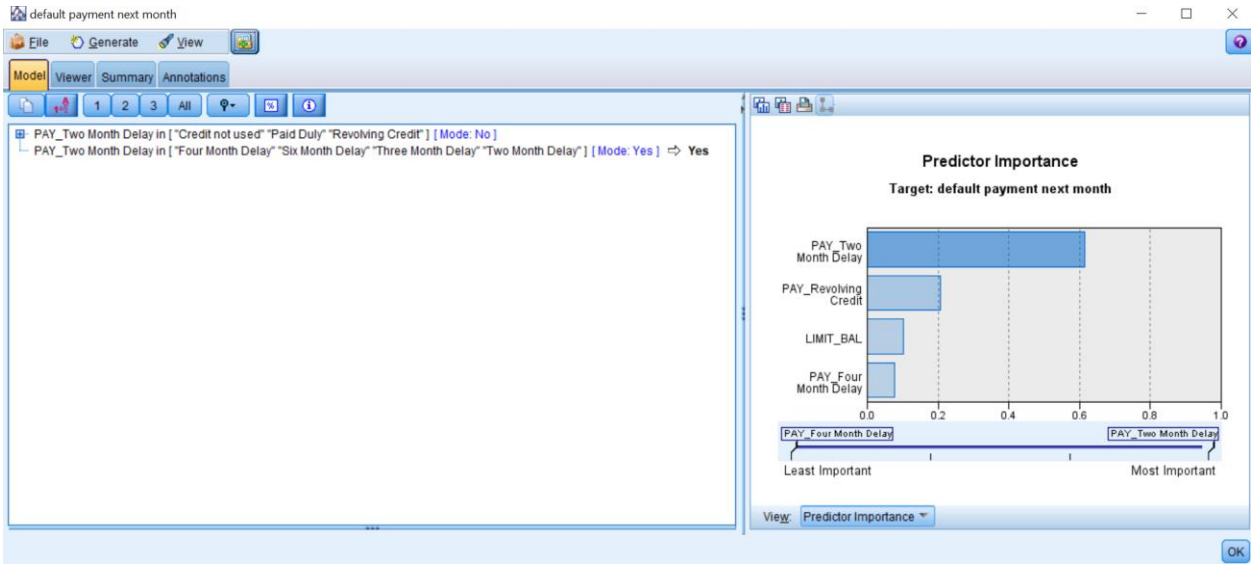
'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$S-default payment next month	0.528	0.057	0.535	0.071	0.531	0.061

Linear


default payment next month
File
Generate
View
Preview
Model
Settings
Summary
Annotations
Collapse All
Expand All
Analysis
Analysis of default of credit card clients_cleaned.xls (Apr 16, 2018 12:51:45 PM)
Fields
Build Settings
Use partitioned data: true
Partition: Partition
Calculate predictor importance: false
Calculate raw propensity scores: false
Calculate adjusted propensity scores: false
Mode: Expert
Append all probabilities (valid only for categorical targets): false
Stopping criteria: 1.0E-3
Kernel type: Linear
Regularization parameter : 5
Regression precision (epsilon): 0.1
RBF gamma: 0.1
Gamma: 1.0
Bias: 0.0
Degree: 3
Training Summary


Analysis of [default payment next month]
File
Edit
Analysis
Annotations
Collapse All
Expand All
Results for output field default payment next month
Comparing $S-default payment next month with default payment next month
'Partition' 1_Training 2_Testing 3_Validation
Correct 14,443 81.79% 4,936 82.42% 4,858 81.61%
Wrong 3,216 18.21% 1,053 17.58% 1,095 18.39%
Total 17,659 5,989 5,953
Coincidence Matrix for $S-default payment next month (rows show actuals)
'Partition' = 1_Training No Yes
No 13,194 544
Yes 2,672 1,249
'Partition' = 2_Testing No Yes
No 4,468 190
Yes 863 468
'Partition' = 3_Validation No Yes
No 4,423 177
Yes 918 435
OK

K-NN



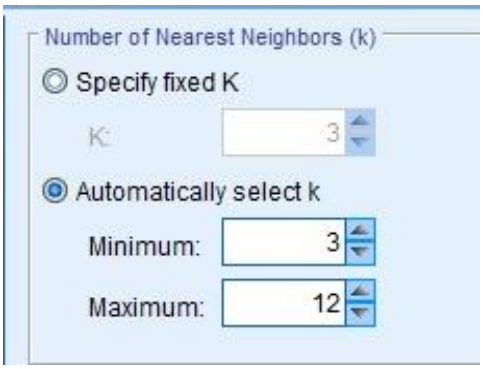


Figure 1: K Selection

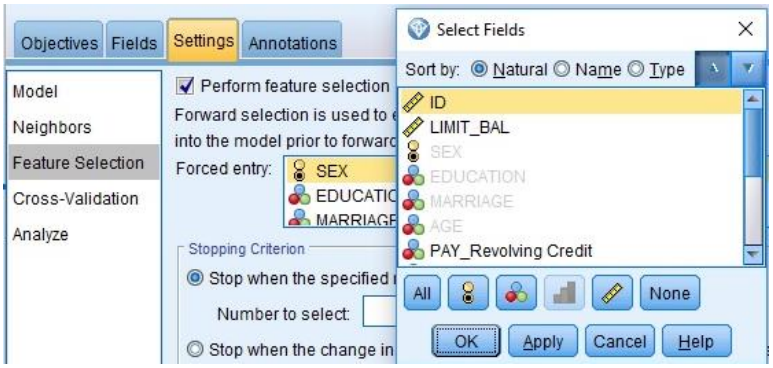


Figure 2: Perform feature selection

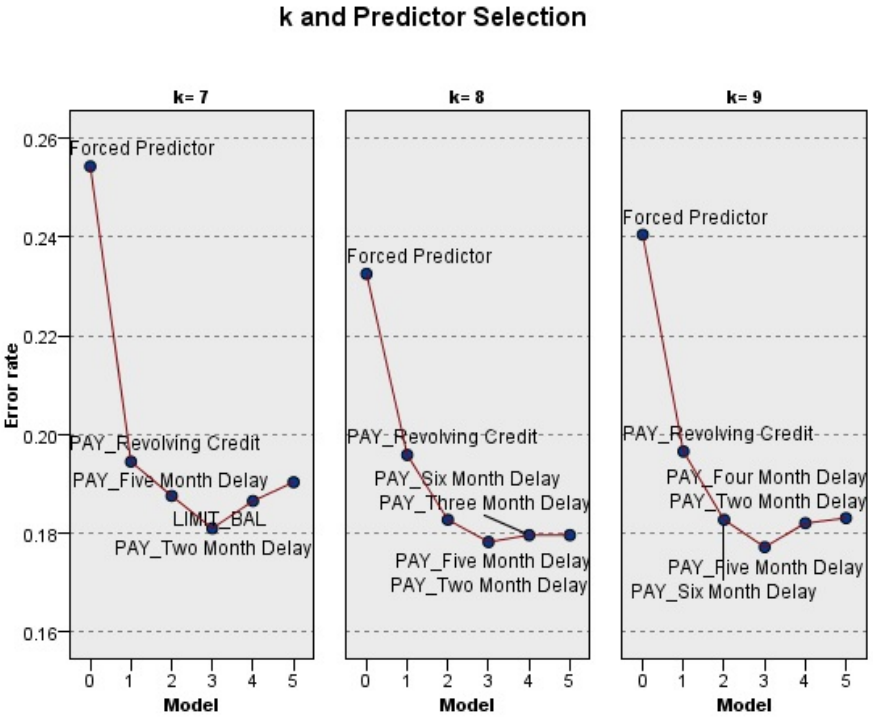


Figure 4: Finding optimal k value by lowering error rate

Graph	Model	Partition	No. Records in Split	No. Fields Used	Overall Accuracy (%)
		2_Testing	5989	9	83.102
		1_Traning	17659	9	82.779
		3_Validation	5953	9	82.059

Figure 5: Model performance for each partition

Logistic Regression

Results for output field default payment next month

Individual Models

Comparing $L-default payment next month with default payment next month

'Partition'	1_Training		2_Testing		3_Validation	
Correct	1,314	79.78%	491	81.83%	491	82.66%
Wrong	333	20.22%	109	18.17%	103	17.34%
Total	1,647		600		594	

Performance Evaluation

'Partition' = 1_Training	
No	0.088
Yes	1.027

'Partition' = 2_Testing	
No	0.053
Yes	1.092

'Partition' = 3_Validation	
No	0.06
Yes	1.16

Evaluation Metrics

'Partition'	1_Training		2_Testing		3_Validation	
Model	AUC	Gini	AUC	Gini	AUC	Gini
$L-default payment next month	0.722	0.445	0.729	0.458	0.714	0.428

Figure 6: Logistic Regression Model Performance

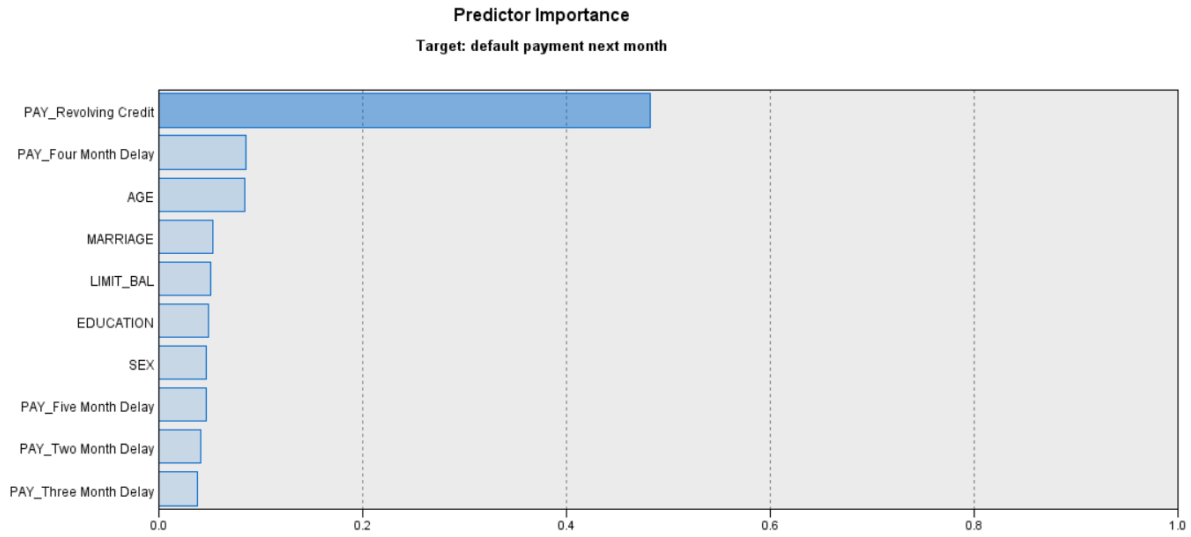


Figure 6: Predictor Importance

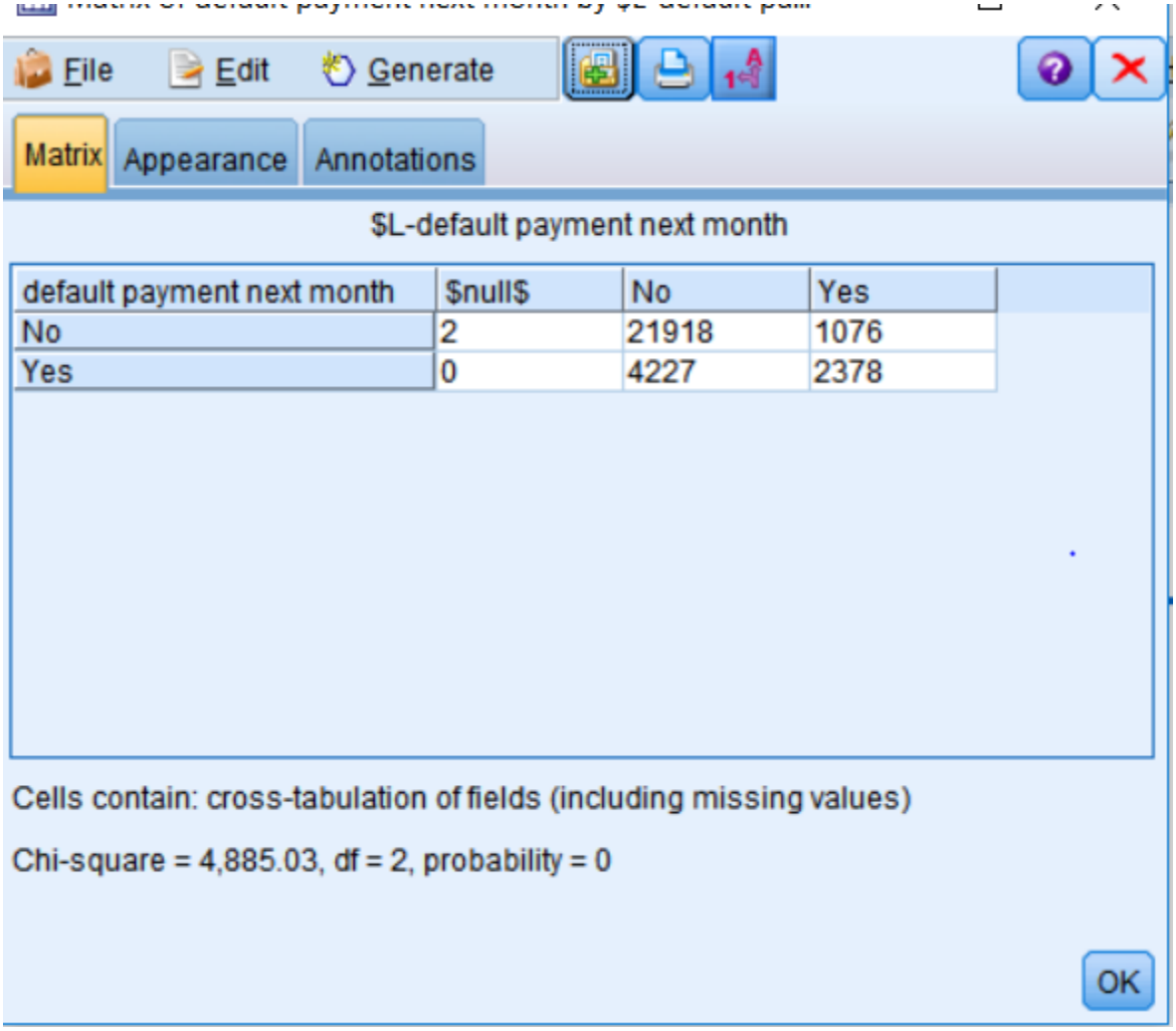


Figure 1 Logistic Regression Matrix