Capstone Report

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1 Introduction

BNP Paribas Cardif is an global insurance company that specializes in personal insurance. Not only do they have to deal with an increasing number of claims, their customers are also expecting them to handle claims as fast as possible. Usually claims go through a number of checks before being approved. However, BNP Paribas Cardif hopes to speed up that process using data science.

2 Dataset

BNP Paribas Cardif provided an anonymized dataset on kaggle.com with two categories of claims described on kaggle.com as follows:

- 1. claims for which approval could be accelerated leading to faster payments
- 2. claims for which additional information is required before approval

The goal is to predict the category of a claim based on information available early in the claims process.

Link: https://www.kaggle.com/c/bnp-paribas-cardif-claims-management

3 Initial Look

Three files are provided:

- $1.\ {\rm train.csv}$ training set with target (dependent variable)
- 2. test.csv test set without target
- $3.\,$ sample submission.csv - sample submission with correct format

The dataset contains 133 features named 'ID', 'target', and 'v1' through 'v131'. There are both categorical and numerical features. None of the categorical features are ordinal (specified on kaggle).

The main limitation of this dataset is that the features are anonymized. Because of this, we can't use domain knowledge to eliminate features or predict the distributions of certain features.

4 Data Wrangling

Main steps for data wrangling:

- 1. Remove all features that had more than 25 percent NA values
 - Went from 131 features to 29 features
- 2. Remove the outliers in continuous variables and replaced with NA values
- 3. Replace the NA values in continuous variables with the mean
- 4. Replace the NA values in categorical variables with the mode
- 5. Remove features with zero/near-zero variance
 - Went from 29 features to 26 features
- 6. Remove categorical variables with more than 20 categories
 - Went from 26 features to 22 features
- 7. Remove features with perfect multicollinearity
 - Went from 22 features to 19 features
- 8. Remove features that were highly correlated with others using VIF
 - Went from 19 features to 14 features

The features remaining include, v10, v12, v21, v24, v47, v50, v52, v62, v66, v71, v72, v91, v114, v129.

5 Feature Enrichment

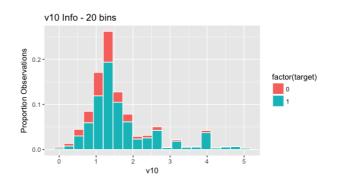
The main methods for feature enrichment used were Weight of Evidence (WoE) and Information Value (IV).

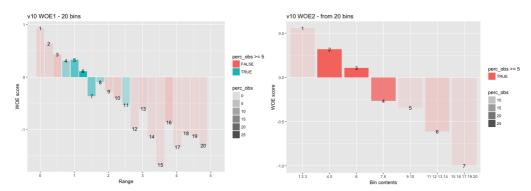
For continuous variables, initially we take the range and divide it up into 20 equally spaced bins. We calculate the weight of evidence for each of those bins and graph WOE against the bins, also including information about what percentage of total observations are contained in each bin. The rule of thumb is that every bin should contain at least 5 percent of the total observations. So from the original bins, adjacent bins were combined if either they had similar WOE scores or if they both contained fewer than 5 percent of the observations.

Similarly for continuous variables, we assign each category as a bin. If categories have similar WOE scores, they are combined.

5.1 v10 - Continuous feature

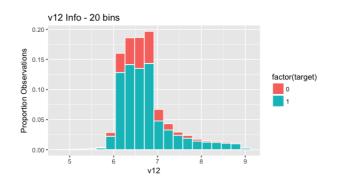
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.000001	1.050328	1.312910	1.615455	1.838074	5.032824

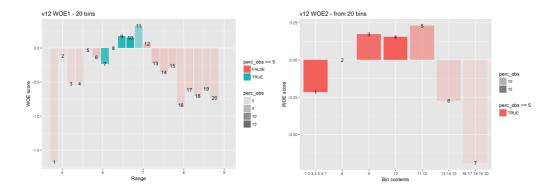




5.2 v12 - Continuous feature

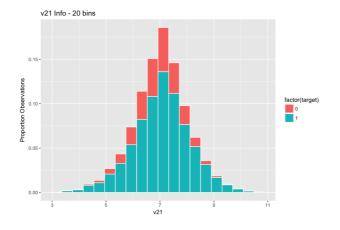
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-4.799	-6.324	-6.615	-6.725	-6.893	-8.972

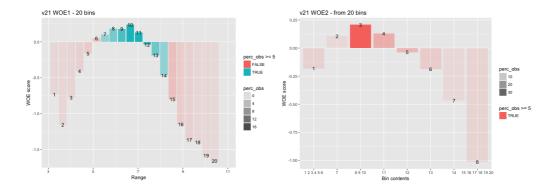




5.3 v21 - Continuous feature

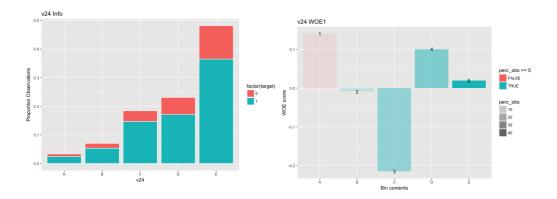
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
-3.268	-6.423	-7.035	-7.032	-7.661	-10.788	





5.4 v24 - Categorical feature (TOSSED)

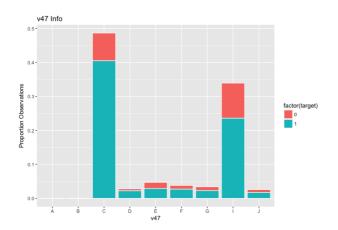
A	В	С	D	Е
1904	4014	10528	13190	27525

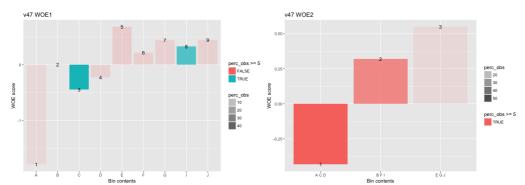


The IV for the initial binning of v24 was 0.01096248 which is considered not useful for predictions so this variable was tossed.

5.5 v47 - Categorical feature

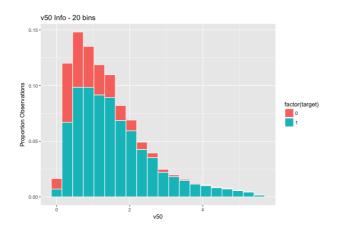
A	В	С	D	Е	F	G	I	J
20	25	27811	1609	2693	2177	1953	19392	1481

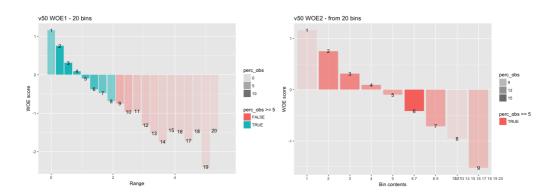




5.6 v50 - Continuous feature

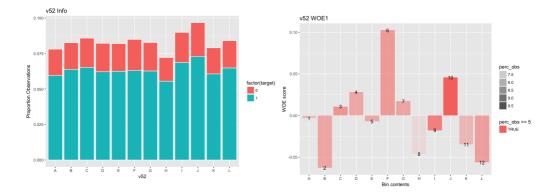
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.000001	0.658793	1.216345	1.460364	1.971976	5.549116





5.7 v52 - Categorical feature (TOSSED)

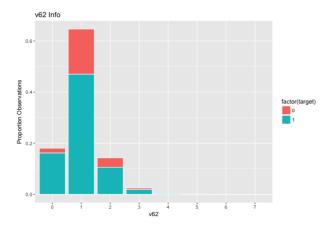
A	В	С	D	Ε	F	G	Н	I	J	K	L
4462	4720	4905	4697	4685	4854	4728	4125	5136	5529	4515	4805

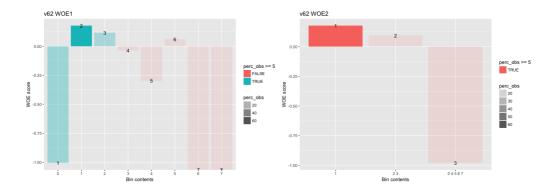


The IV for the initial binning of v52 was 0.002302835 which is considered not useful for predictions so this variable was tossed.

5.8 v62 - Categorical feature

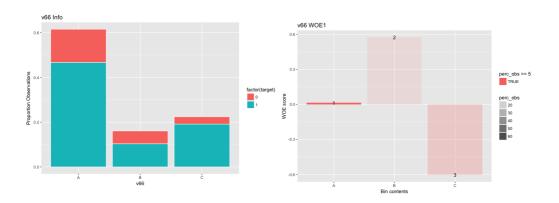
0	1	2	3	4	5	6	7
10314	36965	8161	1412	238	48	22	1





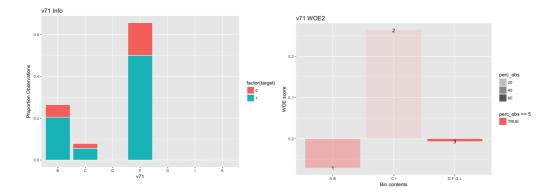
5.9 v66 - Categorical feature

A	В	С
35164	9188	12809



5.10 v71 - Categorical feature (TOSSED)

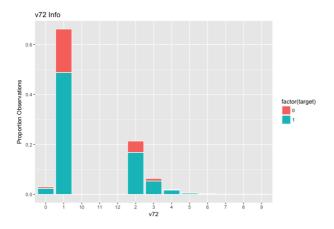
A	В	С	D	F	G	I	K	L
0	15111	4516	1	37519	3	10	1	0

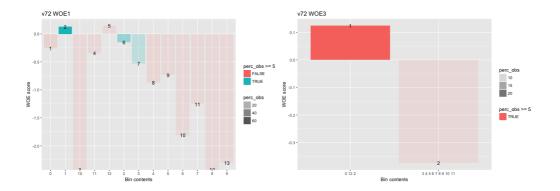


The IV for the binning with no empty bins of v71 was 0.0059342 which is considered not useful for predictions so this variable was tossed.

5.11 v72 - Categorical feature

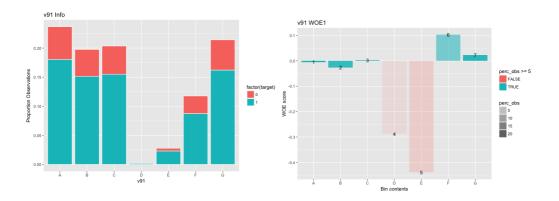
0	1	10	11	12	2	3	4	5	6	7	8	9
1708	37824	30	11	15	12197	3635	1129	329	143	61	46	33





5.12 v91 - Categorical feature (TOSSED)

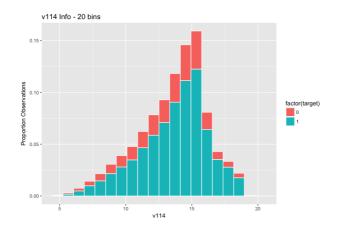
A	В	С	D	Е	F	G
13534	11300	11638	126	1588	6729	12246

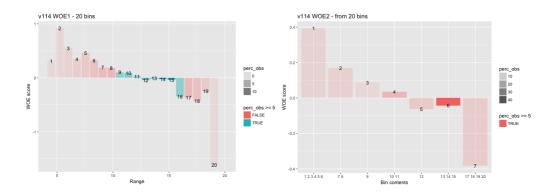


The IV for the binning with no empty bins of v91 was 0.006104932 which is considered not useful for predictions so this variable was tossed.

5.13 v114 - Continuous feature

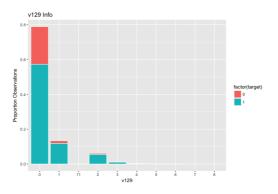
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
4.479	11.981	14.040	13.572	15.371	19.820

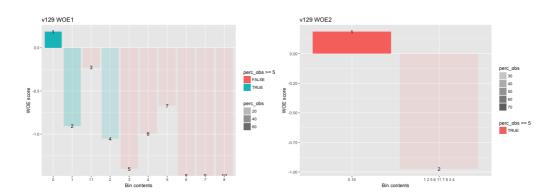




5.14 v129 - Categorical feature

0	1	11	2	3	4	5	6	7	8
45103	7630	5	3499	685	183	29	25	1	1





Variable	IV	Cimpificance
variable	1 V	Significance
v10	0.1461525	**
v12	0.05399145	*
v21	0.08575021	*
v24	0.01096248	TOSS
v47	0.1573225	**
v50	0.4500647	***
v52	0.002302835	TOSS
v62	0.146551	**
v66	0.1282981	**
v71	0.00593427	TOSS
v72	0.04107886	*
v91	0.006104932	TOSS
v114	0.03501795	*
v129	0.175497	**

6 Machine Learning