Semester Project

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Abstract
Include abstract here – A summary of your work

Keywords
Keyword1 — Synergy — Keyword3

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Contents

1. Problem and Data Description

First we want to get a general idea of our data set and get a deeper understanding of the underlying structure.
There are 59 named features or variables for our data set.
With 892816 observations for training and 595212 for test
There are no duplicate observations.
Features that belong to similar groupings are given certain feature names.
- Ind: related to individual or driver
- Reg: related to geographical region
- Car: related to car being insured
- Calc: are calculated features done by Proto themselves
Postfix descriptors describes the features data type.
- Bin: Binary (1 or 0)
- Cat: Categorical *Note: the dataset has the categorical data already convert into factors and then integers
- All other variables are either integer or numeric
As stated the Data Types are numeric and integer, with integer being the predominant type 49 to 10.
Missing values are represented by -1.
In total, there are 13 variables with missing values.
There is Target feature which denotes the binary classification for that observation. This feature is the feature we are trying to learn/predict for the test data.
There is an ID feature which is an anonymized identities of insured drivers.

Porto Seguro's Safe Driver Prediction has 59 variables and 1.3 million observations, which qualifies as a good candidate for reducing overall dimensions of the data to significantly increase the speed of analysis techniques at the cost of more upfront data processing.

There are only 21694 cases of classification 1, which is 3.64 percent of the observations in the training data set, showing significant skew in the expected class towards a "0" prediction.

2. Data Preprocessing & Exploratory Data Analysis

2.1 Feature Engineering

As even missing data can be significant, a new feature was added to the data set. This feature was the count of missing values for each entry before these missing values were processed. This technique allows the retention of the potentially useful information provided by the missing values.

2.2 Handling Missing Values

After observing the summaries of each variable in our data sets, it was clear that variables ps-car-03-cat and ps-car-05-cat contained mostly missing values for each data set. Because we later used a missing value replacement techique to process the data, applying this techique to variables with mostly missing values may have overfitted and affected the outcome of future analysis, thus both because of this possible overfitting and that useful information may be captured in the engineered feature of missing value counts, these columns were removed before proceeding with our NA replacement technique.

After the columns with mostly missing were removed, we replaced missing values with the mean of it's variable using the R package "mice".

2.3 Exploratory Data Analysis

To reduce the complexity of future analysis techniques, we used the prcomp function from base R to perform PCA dimensionality reduction on our data. After the transformation, the first 16 principle components represented over 99 percent

of the the data's variance. Using this as a reasonable cut-off, we proceeded forward using only these first 16 principle components.

Note: To perform this transformation correctly, the test and train data must be transformed together and split after the dimensions have been reduced.

3. Algorithm and Methodology

Once the data was processed, we used the Naive Bayes algorithm to form our model. We tested it with both the implementation from the e1071 package and the caret package. The caret package implementation ended up being more powerful since it allowed for easy cross validation. We used 10 folds, trained on our pca- reduced data set.

We wanted to test a second classifier, so we chose XGBoost, since it had been used successfully by a number of people previously. Despite trying a number of different tree depths and iteration limits, we were unable to have it perform better than the Naive Bayes did.

4. Experiments and Results

Since we had access to multiple submissions on Kaggle, we were able to use their fitness measurements to test our predictions. When we did PCA, we originally kept 95% of the variance, and used that to run Naive Bayes. When we submitted this, we only got a GINI score of .125, but when we increased the total variance to 99%, the score jumped up to .20566.

5. Summary and Conclusions

Acknowledgments