A Hybrid Machine Learning Model with Cost-function Based Outlier Removal and Its Application on Credit Rating

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Abstract. This paper establishes a methodology to build hybrid machine learning models, aiming to combine the power of different machine learning algorithms on different types of features and hypothesis. A generic cost-based outlier removal algorithm is introduced as a step of pre-process of training data. Using this methodology, an experimental hybrid machine learning model is implemented for a crediting problem, which combines three types of machine learning algorithms SVM, DT and LR. Different metrics of training time, recall, precision, F1 score, and AUC are evaluated and compared with the results from single model of single SVM, DT, and LR. The new hybrid models in general shows improvement in performance on multiple metrics. this study further demonstrated that one learning model may work well on certain type of variables but not as effectively on other variables. Well defined procedures can be followed to create hybrid models to combine the power of different learning models, which are superior in dealing with dataset with complicate feature selection. This methodology can be explored with other algorithms and applications.

1. Introduction
In the credit industry, accurate credit scoring models are of great significance to financial institutions. Banks and credit companies often have sizeable loan portfolios. Even the slightest improvement in credit scoring accuracy can result into significant future savings, reducing lenders’ risk [1].

The main objective in credit scoring models is to determine whether the borrower is at risk of defaulting based on predictor variables such as income, FICO score, and loan interest rate. Creditors typically construct models based on pre-existing data with relating predictors to default rates. The push for better credit score models has led to development and research into various techniques, particularly in machine learning, as credit scoring is well suited for supervised learning [2].

The credit scoring problem can be approached through a machine learning framework structured in the following way. Given a set of debtors, each debtor has a number of characteristics (i.e. annual income, debt-to-income ratio, FICO score, etc.) called predictor variables. Given a dataset $S = \{(x_1, y_1), (x_m, y_m)\}$ where $m$ is the number of samples (borrowers), each borrower $x_i$ has $n$ attributes. $y_i$ indicates status (defaulted or not). This dataset is used to create model $f$. Then for an unknown $x$, which would be a loan applicant, we assign the default status $y$ as $y=f(x)$. The output $y$ is binary, with 1 denoting default (charged off) and 0 denoting normal (paid in full). This framework, in which a model identifies a binary class based on new observations is known as a classification problem.

Many different binary classification techniques have been explored for credit scoring. Common methods are: neural networks (NN), support vector machines (SVM), Logistic regression (LR),...
discriminant analysis, decision trees (DT), and Bayesian networks [3]. West [4] compared five neural network models with other models, concluding that NN models are superior in general and LR is a good alternative. However, the debate over which technique is best for credit models is widely argued, with conflicting data arising. Desai et al [5] concluded that neural networks performed significantly better than linear discriminant analysis, whereas Yobas et al [6] claimed the opposite. Hybrid methods combine different learning models. For example, Lee et al [7] combines discriminant analysis and NN to evaluate credit scoring. Feature selection techniques are emphasize in many studies. Waad et al [8] propose a three-stage feature selection utilizing a variety of filter and wrapper. Somol et al [9] compares different filter and wrapper. Chen et al [10] propose a SVM-based method for feature selection. Chai and Chen [11] look into combining clustering and classification.

It is noted that the accuracy of credit rating models tend to stay in the 80% percentile range, rarely going over 90% [3]. Hence the continued research and development into this topic, as the need for accurate models is ever present.

2. Research objective
The goal of this research is to explore approaches to create hybrid machine learning models and as one application, test it on credit rating issue. We implemented a LR learning method during the data pre-processing to treat categorical variables and similar features. Since the values in the categorical features are normally discretely assigned by human with little consideration into how these values are related to the target variable, they might not truly reflect their weight in the model. Similar features report similar but slightly different information; however, the removal of one of them may result in loss of information. After processing the similar and categorical features through LR, a score is obtained for these features of each sample and is used to replace original features. We also introduce a cost-based outlier removal method in the data pre-process to improve the performance of the model.

We then compared the hybrid models to the no-hybrid models including SVM, DT, and LR.

3. Dataset
We used loan data collected from Lending Club’s Loan Origination Data, a US peer-to-peer lending company that is currently the world’s leading peer-to-peer platform. Lending Club enables borrowers to apply for loans. Loaners can choose to accept or reject loans based on the information provided on the listing. The data covers all loan information from 2007 to 2018, and has 150 variables and over 2.26 million samples, as well as the final loan response (loan status paid off or default).

4. Methodology
A traditional machine learning models are generally broke down into following steps: Data collection, feature selection, data pre-processing, train model and validation, test model, and evaluate accuracy. There are various techniques in each steps. Figure 1 shows the architecture of our model.

![Figure 2. Overall logic structure](image-url)
As shown above, we create a hybrid model that, after initial feature selection, utilizes a Learning Model 1 (could be more than one model) to transform data of categorical features and combine similar features. The original dataset, defined as Dataset 1, is converted into a new dataset, defined as Dataset 2, with some new features whose values are either the logistic regression cost results of one categorical feature, or the logistic regression cost results of a group of similar features. Dataset 2 has no more discrete categorical values and a reduced number of features. Then for comparison purpose, the samples of Dataset 1 and Dataset 2 are split into training, validation and test set in same way. Dataset 1 is processed in the traditional manner for machine learning: treating character and missing values, and normalizing data etc. For Dataset 2, however, will go through an additional cost-based outlier removal process which is described as follows.

Once we choose the machine learning model (Model 2) for final prediction, no matter it is SVM, LR, DT, or other models, we use the training data of Dataset 2 to train this model for the first round, then calculate the cost of each sample in the training set, use standard deviation of the sample cost as a criteria to detect outliers. After the outliers are removes, Dataset 2 becomes a Dataset 2’ which has less number of samples in its training set.

In this study, we use linear regression as learning model 1, and test SVM, LR and DT as learning model 2 individually. The following sections will discuss the steps of our methodology in detail. The programs are implemented with Python.

5. Data pre-process

5.1. Sample selection

The raw data consist of information on borrowers and their loan statuses: "current", "fully paid", "charged off", "late", etc. Since the focus of this model is to determine between “good” loan applicants (“fully paid”) and “bad” or risky applicants who defaulted on their loan (“charged off”), we filtered for those two statuses, creating a data set of 1.3 million loan samples.

5. 2. Feature selection

The first step in feature selection is to remove unnecessary features, such as applicant’s website url (‘url’), or membership ID number (‘member_id’). These features don’t have an effect on the credit score, as they serve as basic information for the lenders to view. At Lending Club, borrowers can receive loans by putting a loan listing. Investors than can search and select loans based on the information provided. The original data contains some features which are not accessible to the investor during the loan application. Those features are excluded from our dataset.

The next step treat missing values. Features which miss over 30% of their data are excluded. The other missing values are replaced with average value of the feature.

In next step, we removed redundant features that overlapped with other categories. For example, the information for loan grade is incorporated in the loan subgrade, creating repetition. The feature ‘grade’ has categories from A-G (i.e. C), however ‘sub_grade’ is a further breakdown of grade, assigning a number from 1-5 to each letter (i.e. C2). Therefore, ‘sub_grade’ already contains the information from ‘grade’ and in fact is much more specific. Several other features too are repetitive in this manner, so we removed them.

The raw loan data set from Lending Club initially had 150 variables. After feature selection, 36 variables remained. The reduced data is denoted as Dataset 1.

5.3. Assign values to categorical features

The 36 variables in Dataset 1 are denoted with a mix of character and numerical values. We assign a value to each group in a particular categorical feature. For example, ‘loan_status’, which is our response column, is formatted as “Fully Paid” or “Charged Off”. We assigned {1} for charged off, and {0} for fully paid.
5.4. Logistic-regression based feature treatment

Hybrid methods combine different machine learning techniques in order to improve the performance of the model. In our model, we use logistic-regression-learning algorithm as learning model 1 and combine it with other models. When re-examining the remaining 36 features, several features contain similar information. For example, one feature lists the number of revolving accounts while another lists the number of revolving accounts with a balance greater than zero. Although these variables could be redundant, removing one might result in loss of valuable information. However, keeping both might lead to weaker performance of the model, we combine features with similar information by training an LR model. The LR model returns the probability of being classified as 1 for each sample. These probabilities are our combined “score” for the two predictor variables. The new column of the probability score is used to replace the original two features. For categorical variables, a numerical value will be assigned manually. For example, the states of applicants are assigned a number sequentially based on its alphabetical order. However, these numbers have no intrinsic meaning and do not reflect a state’s weight on predicting target variable. Therefore, in a similar manner we extract the target variable and used LR learning to obtain a probability scores, which replace the original numbers and have the probability information encoded in them. The resulting dataset is denoted as Dataset 2.

5.5. Treating missing values

The absence of values in dataset is a recurrent issue that may be a result of several issues such as human input error or recording mechanism malfunctioning. Prior to applying a credit scoring method, it is critical to pre-treat the data, as missing values will throw off the learning model. One possible approach is to simply ignore and drop the missing numbers from the original dataset. Another way is to replace NaN values, whether through mean substitution, or regression. In this paper, mean substitution is utilized; the mean of a particular feature is found, the NaN values of that particular feature are replaced with the calculated mean.

5.6. Normalizing data set

Financial organizations collect a wide variety of consumer variables, which can have drastically different ranges in the raw data. For example, age can range from 0-100, whereas yearly income can range from 0-100,000, or higher. Due to the larger raw data values, the machine learning model might improperly view yearly income as more significant. Thus, after treating error values in the dataset, it is necessary to normalize the data. Several methods of data normalization can be used, such as standard score ($z$-score), and min-max. In this paper, min-max normalization is used.

5.7. Outlier removal and class weight

After the data normalization, we introduce a cost-based outlier removal process, which evaluates the cost function of each sample, and removes samples based on a determined threshold. The cost function measures the error in the model’s prediction, expressed as the difference between the predicted and actual value. Machine learning models aim to minimize the cost function in order to improve performance. For LR and DT, we set a threshold at 95% such that a sample is labelled and removed if it is wrongly classified with a possibility greater than 95%. For SVM, we set the threshold at $2.3\sigma$ ($\sigma$ is the standard deviation of the cost of all the samples) such that if a wrongly classified sample is removed if it’s cost is over $2.3\sigma$. Once the samples are removed, we reset the models and retrained using the reduced training set.

Lending Club’s dataset is a skewed dataset with about 80% of the data had the class label {0}, the imbalanced data can cause learning models to label too many samples as {0}. Therefore, by adding class weight to the data, the model will penalize the misclassifications of the minority class more heavily, resulting in an increased true positive rate. In this study we adjust class-weight to find an optimum weight about 1.8 on the minority class.

To demonstrate the effect for this outlier removal process and class-weight, we construct a two-variable classification problem and Figure 2 illustrates process with SVM as learning model.
Figure 2. Effect of outlier removal and class weight

Figure 2. (a) shows a SVM model with an initial outlier of red dot in the lower left corner. The hyperplane is evidently skewed towards the outlier, causing several blue inputs to be misclassified, as the hyperplane attempts to incorporate the red outlier. After executing the cost based outlier removal procedure and train the SVM again, In Figure 2. (b), we can see how the hyperplane becomes more vertical and separate the two groups better. While the model is improved, there are still misclassified points. Figure 2. (c) shows that after adding class weights, there is one less misclassified blue input.

6. Training and testing

During the training process, 20,000 samples are randomly selected from both Dataset 1 and 2. The training set is then split into 80% training and validation, and 20% testing. We ran 50 trials, where each trial created three traditional modal of LR, SVM and DT and three new models with LR, SVM and DT as predicting model but have our modification integrated in. After 5-fold cross validation. The models are run on test set.

7. Results

After each trial, we collect the test metrics of each hybrid model and compare them with those from unmodified model. A typical result of one trial is shown in table 1, where the postfix “-H” denotes the result from hybrid model, “-O” denotes the results from unmodified model.

| Index | Model | ExecTime | TP  | TN   | FP  | FN  | Outliers |
|-------|-------|----------|-----|------|-----|-----|----------|
| 3     | DT-O  | 0.3675   | 517 | 2938 | 265 | 280 | 0        |
| 3     | DT-H  | 0.295286 | 527 | 2970 | 256 | 247 | 176      |
| 3     | LR-O  | 0.202038 | 458 | 3076 | 131 | 335 | 0        |
| 3     | LR-H  | 0.169056 | 604 | 2975 | 214 | 207 | 40       |
| 3     | SVM-O | 7.602738 | 559 | 3018 | 189 | 234 | 0        |
| 3     | SVM-H | 7.099988 | 651 | 2914 | 279 | 156 | 234      |

Table 1. Training time, TP, TN, FP, FN and number of outliers of one trial
We collect training time (execTime in seconds), TP, TN, FP, FN and number of outliers removed by hybrid model, then calculate each model’s accuracy, precision, recall, F1-score and AUC values as shown in table 2.

| Index | Model | Accuracy | Precision | Recall | F1 Score | AUC |
|-------|-------|----------|-----------|--------|----------|-----|
| 3     | DT-O  | 0.86375  | 0.661125  | 0.648683| 0.654845 | 0.7859|
| 3     | DT-H  | 0.87425  | 0.673052  | 0.680879| 0.676943 | 0.8003|
| 3     | LR-O  | 0.8835   | 0.777589  | 0.577554| 0.662808 | 0.9356|
| 3     | LR-H  | 0.89475  | 0.738386  | 0.74476 | 0.741559 | 0.9435|
| 3     | SVM-O | 0.89425  | 0.747326  | 0.704918| 0.725503 | 0.9391|
| 3     | SVM-H | 0.89125  | 0.7       | 0.806691| 0.749568 | 0.9499|

Generally, there are improvements in the performance of a learning model when logistic-regression feature treatment and cost-based outlier removal is incorporated in. The improvements are slight but consistent. Table 3 shows comparison of the average numbers of the model metrics

| Model  | AvgTime | Accuracy | Precision | Recall | F1 Score | AUC | Outlier |
|--------|---------|----------|-----------|--------|----------|-----|---------|
| SVM-O  | 7.8201  | 0.8986   | 0.7609    | 0.7215 | 0.7404   | 0.9449| 0       |
| SVM-H  | 7.1821  | 0.8960   | 0.7058    | 0.8259 | 0.7610   | 0.9453| 372.2   |
| LR-O   | 0.2523  | 0.8888   | 0.7914    | 0.6073 | 0.6855   | 0.9399| 0       |
| LR-H   | 0.2025  | 0.8970   | 0.7261    | 0.7820 | 0.7526   | 0.9414| 77.6    |
| DT-O   | 0.3950  | 0.8593   | 0.6443    | 0.6567 | 0.6503   | 0.7801| 0       |
| DT-H   | 0.3298  | 0.8693   | 0.6720    | 0.6725 | 0.6722   | 0.7862| 80.2    |

All models show a decrease in training time after our hybrid method is employed, this is mostly due to the dimension reduction and outlier removal. We discover that the execution time of the model is notably longer for SVM, with an average of 7.8201 and 7.1821 seconds (benchmark and hybrid, respectively), as opposed to fractions of a second for LR and DT. In addition, while SVM has the highest accuracy among benchmark models at 89.86%, LR has the highest accuracy among the hybrid models at 89.70%. The accuracy for SVM decreases by 0.26% for the hybrid method.

For the other four evaluation metrics (recall, precision, F1 score, and AUC), DT shows an increase in all but AUC. In fact, DT has consistently the lowest AUC, as SVM and LR have values over 0.9, where DT has values under 0.8; this demonstrated how the performance of DT models are generally poorer. However, DT is the only model which shows an increase in both recall and precision. SVM and LR follow the expected trend of increased recall and decreased precision. LR had the greatest recall increase at 0.1747, indicating that the hybrid LR model is better at predicting the {1}, or default, class. This translates to lower loss for companies, as accurately classifying “risky” borrowers is more important than accurately classifying “good” borrowers. LR shows the greatest improvement in performance, as the difference in AUC is +0.2559.

8. Conclusion and future research
Based on the results of the research, our hybrid method of logistic-regression-based feature treatment, cost-based outlier removal algorithm combined with SVM, DT, LR model are able to reduce variable dimension, detect and remove outliers with improved performance. This study provides a generic approach to refine machine learning algorithm and can be extended to other learning models. This study also provides an evidence that a learning model may work well on certain type of variables but not as effectively on other variables. Hybrid models combine the power of different learning models and are superior in dealing with dataset with complicate feature selection.
However, since we only reduce a small fraction of variables and only test on hybrid model consisting of LR SVM and DT, the performance improvement in this study are very small. It is believed that more improvements can be achieved by reducing more variables, different combinations of traditional learning models. Our data is from a public source, and may not be as comprehensive as data collected by private credit companies. In the future, more research can be conducted on neural networks. In addition, other outlier removal techniques such as wavelet-based outlier removal will be explored as well.

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