Fraud Analytics : Project 3

Transaction Fraud

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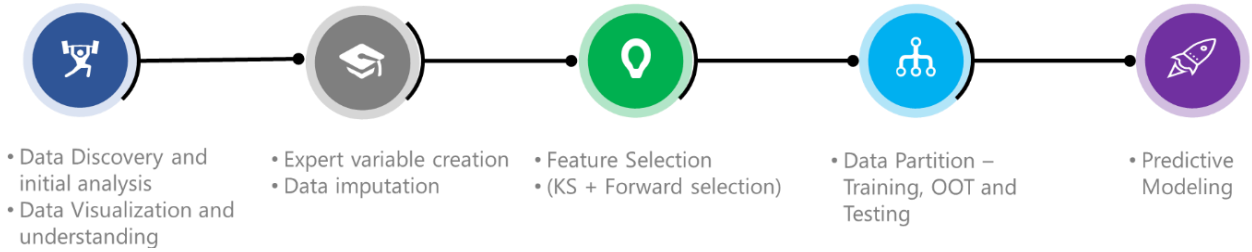
1. Executive Summary

This report provides an analysis and evaluation of Card Transaction Data for detecting fraud using supervised machine learning methods. The original data set contains 96,708 records of card transactions with 10 variables of transaction details such as card number, date of transaction, merchant ID and description, transaction type and amount of transaction.



Process Overview

The general process of analysis follows data cleaning and manipulation, building expert variable, selecting important variables, applying fraud algorithms, calculating fraud scores and evaluating results. We divided the dataset into training, testing and out of time and continued to evaluate the fraud score for each of these brackets.

The tools used include R and Excel, and some of the algorithms used for analysis are Bootstrap Forest (aka Random Forest), Boosted Trees, Neural Networks, Naïve Bayes and Logistic Regression. These five models were built and tested using R and their respective performances were recorded. Among all the models built, Random Forest with 150 trees exhibited the best results. The estimated ROI using this model was $231,710.

Using this best model, Fraud Detection Rate for training set was 71.5%, for testing set it was 68.4% and for out of time set it was 68.3%. Through our analysis we could further identify that there were several expert variables that were strong predictors of fraud. Detailed examination of the important features selected from different algorithms indicates that fraudulent records typically have unusual geographical appearance.

2. Data Overview

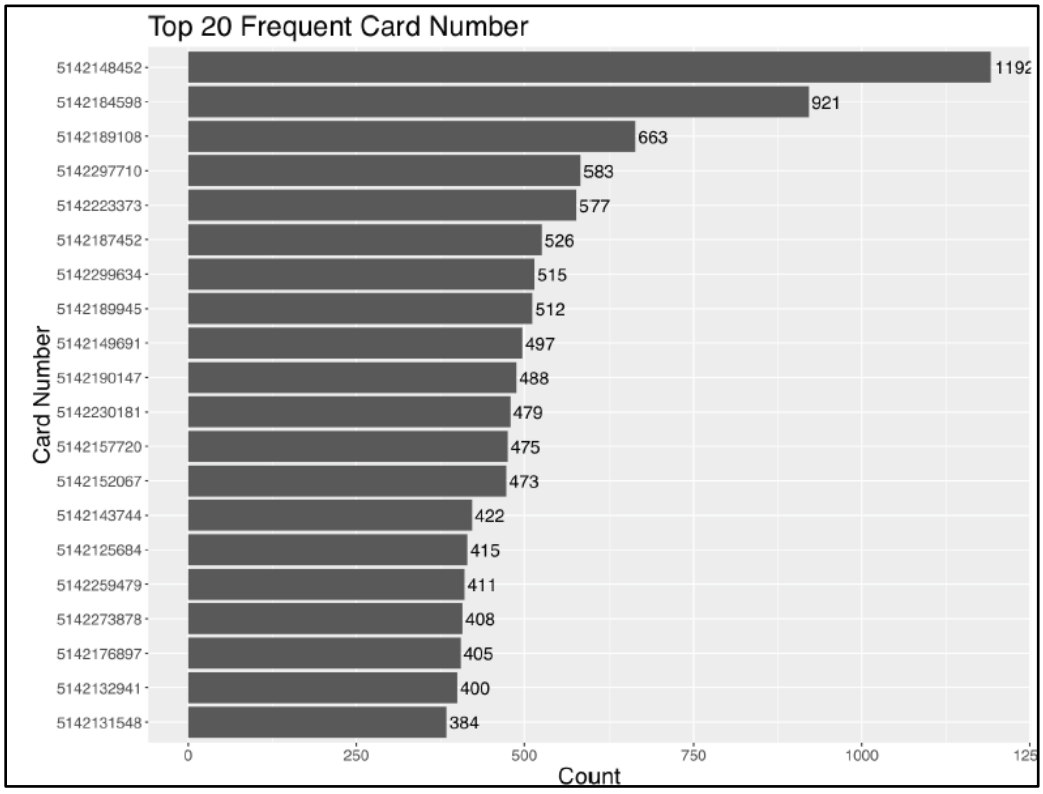
Card payment data is a dataset containing 96,708 records of card transaction from 2010-01-01 to 2010-12-31. It includes information about card number, date, merchant's number, description, state, zip code, transaction type, and amount. Every record is also labeled as fraud or not. In total, there are 298 labeled fraudulent records.

10 variables in total – 1 numeric, 7 categorical, 1 text, 1 date
Numeric: amount
Categorical: recordnum, cardnum, merchnum, merch.state, merch.zip, transtype, and fraud
Text: merch.description
Date: date

Following is the description of the variables we consider to be the most important. The complete Data Quality Report can be found in appendix.

2.1 Description of important variables

2.2.1 cardnum
cardnum is a categorical variable. It is the number of the card used for the payment.
Distribution
100% populated and 1644 unique values. The following plot shows top 20 frequent card numbers

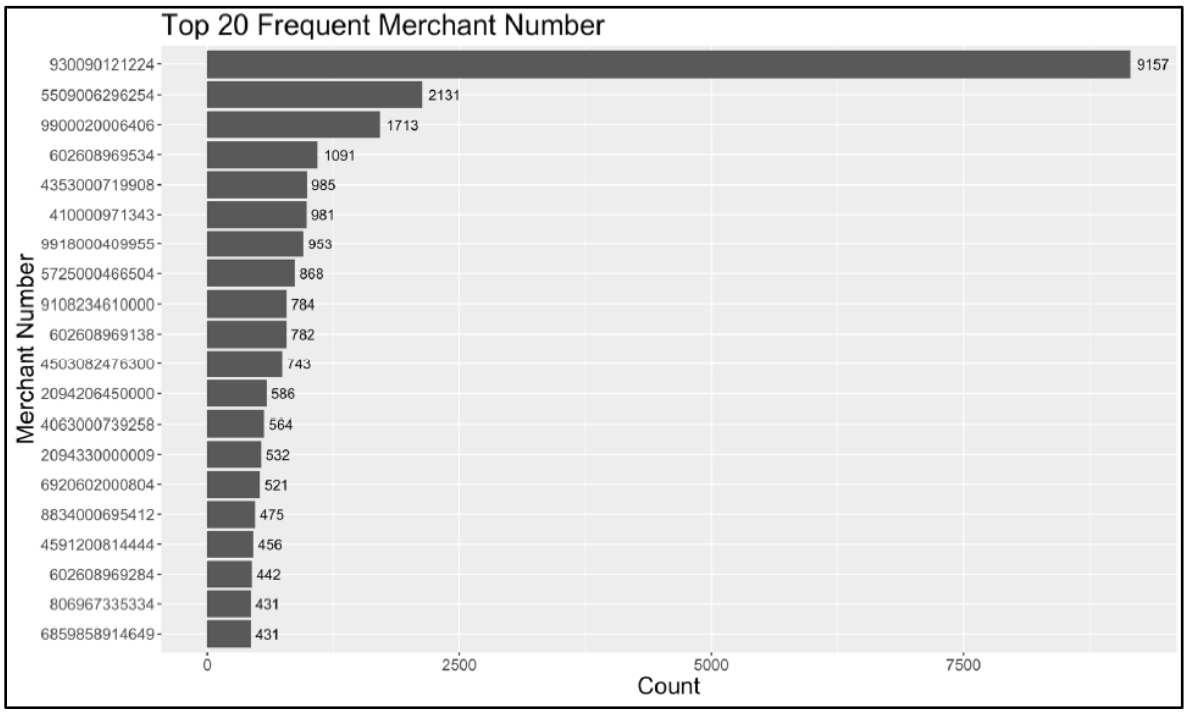


2.2.2 merchnum

merchnum is a categorical variable. It is the merchant number involved in the payment.

Distribution

96.5% populated with 13,090 unique values. There are 3,375 missing values, which includes the number of 0's. The following plot shows top 20 frequent merchant numbers.



2.2.3 merch.state

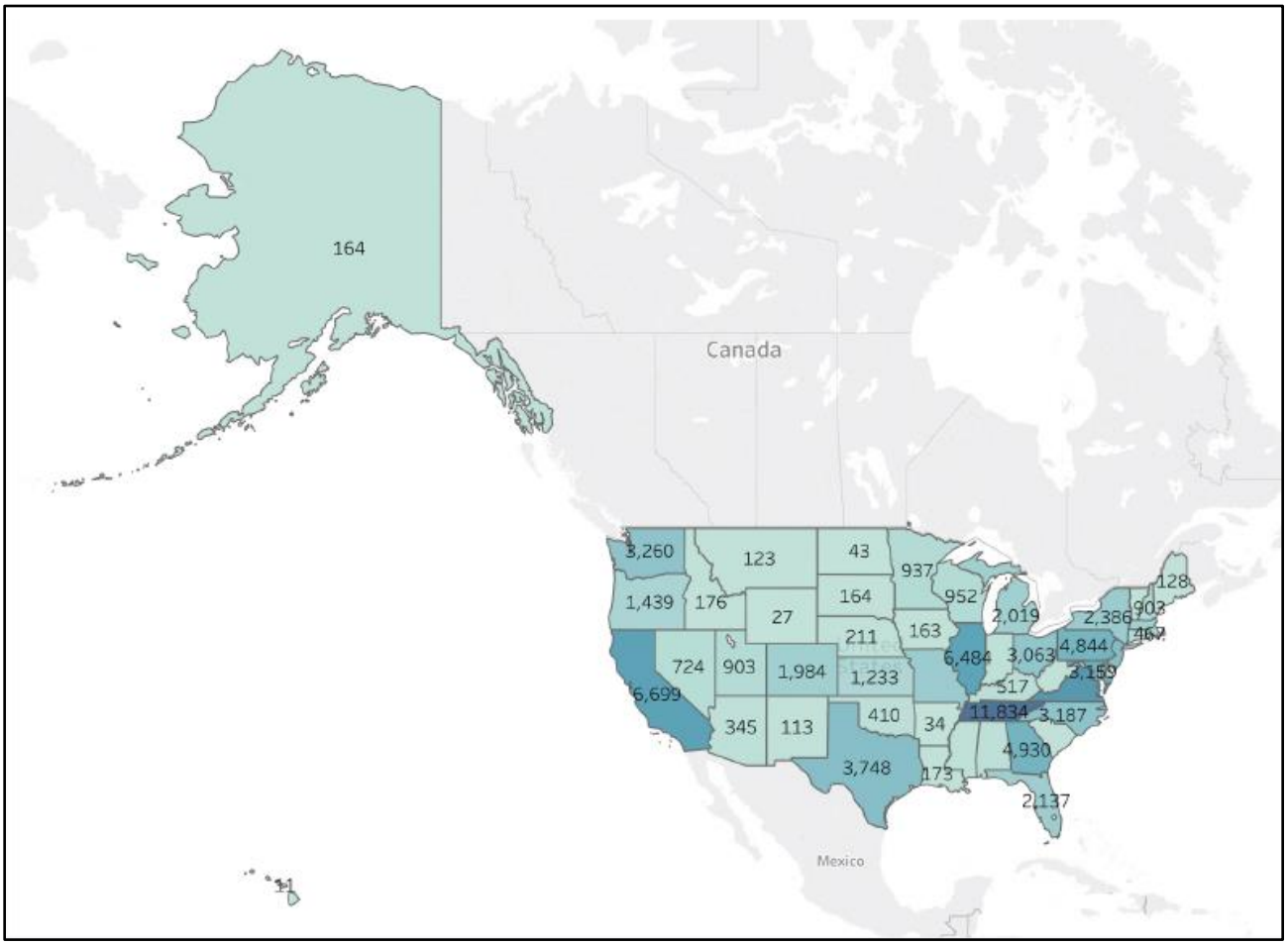
merch.state is a categorical variable, indicating the abbreviations of US states of the each of the merchant.

Distribution

98.7% populated with 60 unique values. 51 values stand for regions in the United States, 50 states and District of Columbia. 7 values stand for Canada. Apart from these, there are 1,199 missing values, and 1 invalid value US. Distribution of states is showed in the following table. States in Canada are marked in blue. Invalid and missing values are marked in red. Regions in the United States are in black.

	AB	AK	AL	AR	AZ	BC	CA	CO	CT
1016	5	164	343	34	345	23	6699	1984	949
DC	DE	FL	GA	HI	IA	ID	IL	IN	KS
3159	70	2137	4930	11	163	176	6484	244	1233
KY	LA	MA	MB	MD	ME	MI	MN	MO	MS
517	173	2075	3	5344	128	2019	937	2415	244
MT	NC	ND	NE	NH	NJ	NM	NS	NV	NY
123	3187	43	211	903	3904	113	5	724	2386
OH	OK	ON	OR	PA	PQ	QC	RI	SC	SD
3063	410	137	1439	4844	14	4	467	153	164
TN	TX	US	UT	VA	VT	WA	WI	WV	WY
11834	3748	1	903	7698	85	3260	952	181	27

The following picture displays distribution by states in the United States. We can clearly see that TN has the largest number of records (11,990).



Details for merch.state with colors showing Number of Records

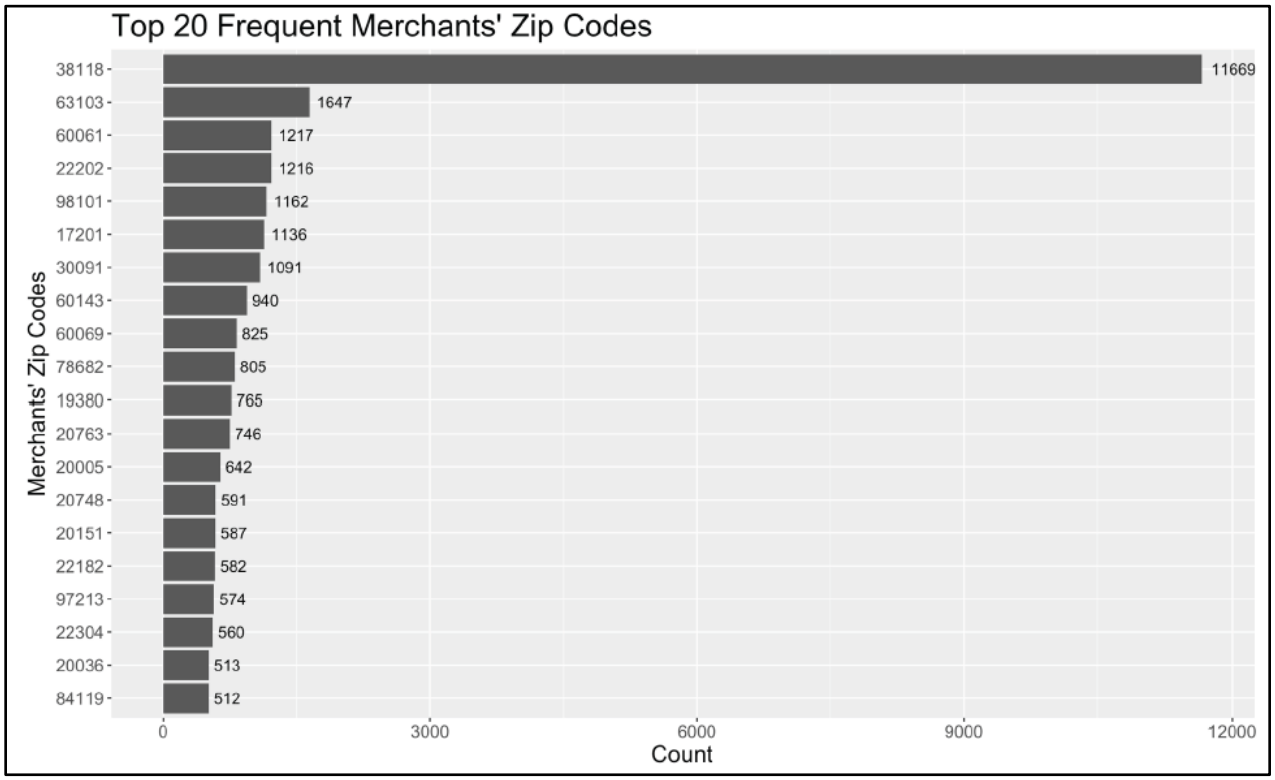
2.2.4 merch.zip

merch.zip is a categorical variable, indicating the zip code of the merchant.

Distribution

95.2% populated with 4567 unique values. 86.99% values have invalid 5-digit zip code. The following plot shows top 20 zip codes.

Although there is one zip code "38118" appears 10 times more than other values, it is in TN, which is the most frequent states; hence we do not treat it as a frivolous value.



3. Handling Missing Values

According to data quality analysis, three variables -- merchnum, merch.state and merch.zip are not 100% populated, with missing values and 0's. We assigned values to these fields based on merch.description. We considered records with different merch.description as different merchants, and assumed that each merchant should have a unique merchant number, be in one state, and only have one zip code. Since all these three variables are categorical, we assigned unique values in these fields according to merch.description, and those values were designed to be quite different from other existing values, therefore easy to recognize. Missing values and 0's in merchnum were replaced by strings from 'M1' to 'M771', missing values in merch.state were substituted by numbers from '1' to '150', and NA's in merch.zip were replaced by strings from 'M1' to 'M644'.

4. Variable Creation

We created 130 expert variables and we kept 40 variables after KS.

Since this analysis involves time, with limited data, we chose four different time windows, 3, 7, 14 and 28 days. The rationale is to capture more (and different types of) fraudulent records that might be detected in those time windows.

Furthermore, we kept 25 variables after lasso, we use these 25 to train our models.

Variable Name	Description/Formula
avg_amount_cardnum_30	Average of consumption amount with same card number within 30 days
avg_amount_cardnum_15	Average of consumption amount with same card number within 15 days
avg_amount_cardnum_7	Average of consumption amount with same card number within 7 days
avg_amount_cardnum_3	Average of consumption amount with same card number within 3 days
avg_amount_cardnum_1	Average of consumption amount with same card number within 1 days
max_amount_cardnum_30	Maximum of consumption amount with same card number within 30 days
max_amount_cardnum_15	Maximum of consumption amount with same card number within 15 days
max_amount_cardnum_7	Maximum of consumption amount with same card number within 7 days
max_amount_cardnum_3	Maximum of consumption amount with same card number within 3 days
max_amount_cardnum_1	Maximum of consumption amount with same card number within 1 days
sum_amount_cardnum_30	Sum of consumption amount with same card number within 30 days
sum_amount_cardnum_15	Sum of consumption amount with same card number within 15 days
sum_amount_cardnum_7	Sum of consumption amount with same card number within 7 days
sum_amount_cardnum_3	Sum of consumption amount with same card number within 3 days
sum_amount_cardnum_1	Sum of consumption amount with same card number within 1 days
avg_weekdiff_amount_cardnum_30	Average of the difference between personal card consumption and average of consumption amount for different day of week with same card number within 30 days
avg_weekdiff_amount_cardnum_15	Average of the difference between personal card consumption and average of consumption amount for different day of week with same card number within 15 days
avg_weekdiff_amount_cardnum_7	Average of the difference between personal card consumption and average of consumption amount for different day of week with same card number within 7 days

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avg_monthdiff_amount_cardnum_30	Average of the difference between personal card consumption and average of consumption amount for different month with same card number within 30 days
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state_merchantnum_7	Count of different state with same merchant number within 7 days
state_merchantnum_3	Count of different state with same merchant number within 3 days
state_merchantnum_1	Count of different state with same merchant number within 1 days

We then built four types of variables using R:

1) **Type I** variables are intended to capture unusual amounts of transaction, both at the card level and the merchant level.
   Example: card_amount_to_avg_3 tells if a particular transaction amount is unusual compared to historical averages of the past 3 days.

2) **Type II** variables are intended to capture unusual transaction frequency during a set period of time, both at the card level and the merchant level.
   Example: card_frequency_3 describes the transaction frequency for each specific card number in the past 3 days

3) **Type III variables** are location related variables, which are intended to capture merchants with different zip codes and states in a set period of time.

Example: zip_with_merchnum_3 tells how many zip codes are related with a particular merchant in the past 3 days.

4**) Type IV variables** are intended to catch card appearance pattern, either for a merchant or for a card holder.
Example: merchnum_per_card_3 tells how many different merchants a card was used for transaction within the past 3 days.

4.1 Type I Variables:

card_amount_to_avg: ratio of transaction amount of a specific card number to its historical average amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific card number in a specific time window was replaced by a neutral value – 1 before building this set of variables.

merchant_amount_to_avg: ratio of transaction amount of a specific merchant number to its historical average amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific merchant number in a specific time window was replaced by a neutral value - 1 before building this set of variables.

card_amount_to_max: ratio of transaction amount of a specific card number to its historical maximum amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific card number in a specific time window was replaced by a neutral value – 0 before building this set of variables.

merchant_amount_to_max: ratio of transaction amount of a specific merchant number to its historical maximum amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific merchant number in a specific time window was replaced by a neutral value - 0 before building this set of variables.

card_amount_to_median: ratio of transaction amount of a specific card number to historical median amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific card number in a specific time window was replaced by a neutral value - 1 before building this set of variables.

merchant_amount_to_median: ratio of transaction amount of a specific merchant number to its historical median amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific merchant number in a specific time window was replaced by a neutral value - 1 before building this set of variables.

card_amount_to_total: ratio of transaction amount of a specific card number to its historical total amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific card number in a specific time window was replaced by a neutral value - 0 before building this set of variables.

merchant_amount_to_total: ratio of transaction amount of a specific merchant number and historical total amount by time window 3, 7, 14 and 28 days. To set a baseline, the first value of each specific merchant number in a specific time window was replaced by a neutral value - 0 before building this set of variables.

4.2 Type II Variables:

card_frequency: transaction frequency for each specific card number by time window 3, 7, 14 and 28 days.

merchant_frequency: transaction frequency for each specific merchant number by time window 3, 7, 14 and 28 days.

4.3 Type III Variables: Location

zip_with_merchnum: number of different zip codes related to a particular merchant in the time windows of 3, 7, 14 and 28 days.

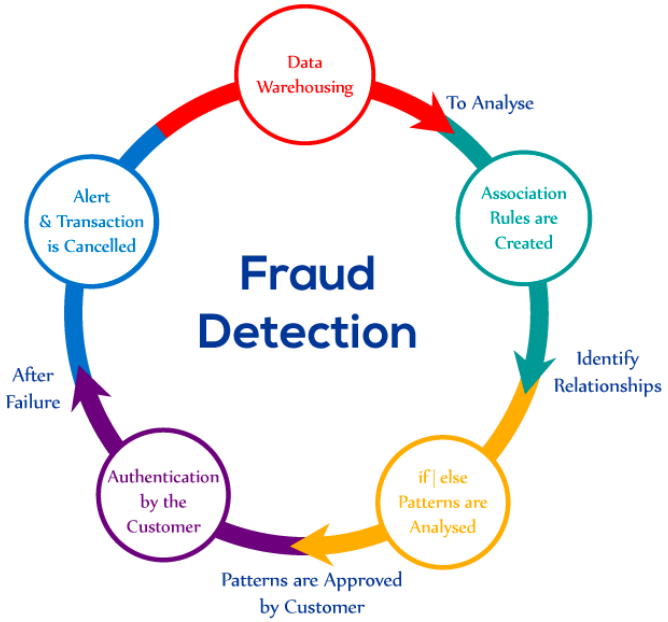
state_with_merchnum: number of different states related to a particular merchant in the time windows of 3, 7, 14 and 28 days.

4.4 Type IV Variables: Purchasing Pattern

cardnum_per_merch: number of different cards associated with a particular merchant in time windows of 3, 7, 14 and 28 days.

merchnum_per_card: number of different merchants associated with a particular card in time windows of 3, 7, 14 and 28 days.

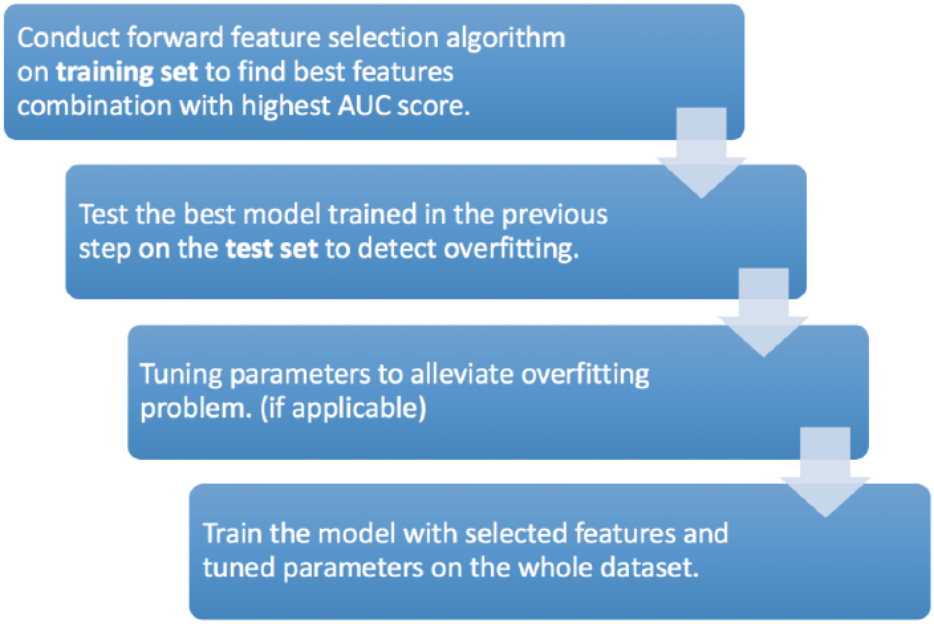
5. Supervised Fraud Algorithm



5.1 Training/Test Set Split

Before training all the models, we first extracted records after the first 28 days, Z-scaled all the features, randomly shuffled the observations, and then split the whole dataset into training, testing and out of time set with the 6:4:2. i.e. First 6 months for training set, next 4 months for testing set and finally last 2 months for the out of time set.

5.2 Forward Feature Selection



5.2.1 Forward Feature Selection Algorithm

We used a wrapper feature selection method called forward stepwise selection algorithm to select features during the modeling process. The algorithm we applied is described below.

Forward Stepwise Selection Algorithm

1. Initialization:
   (a) Let M_0 denote the null model, which contains no predictors.
   (b) Initialize maximum AUC score: $S_0 = 0$.
   (c) Initialize best features combination: F = [].

2. For k = 0, 1, 2, ..., 55:
   (a) Consider all 56-k models that augment the predictors in M_k with one additional predictor. Calculate AUC score for each of them.
   (b) Choose the model with highest AUC score among these 56-k models, and call it M_{k+1}.
   (c) Compare the highest AUC score S found in (b) with S_0,
   if $S > S_0$, update S_0 with the value of S and update F with current feature selections, and enter the next loop step;
   if $S = S_0$, do nothing and enter the next loop step;
   if $S < S_0$, stop the loop.

3. Finalize:
   F is the set of features selected through this forward stepwise selection algorithm, and S_0 is the highest AUC score that ever got during the process.

This algorithm helped us to find the features combination that gives highest AUC score on the training set in a forward-selection manner. We used AUC scores as the comparison criterion, because AUC scores take all classification cut-offs into consideration (i.e. considered all the cases that we predict probability >= p as fraud, where p could be any value between 0 and1), reflecting the overall performance of the classifier in all fraud score quantiles.

5.2.2 Supervised Models

We have tried five supervised models combining the forward feature selection algorithm. The performance metrics of each model are shown below.

Models	AUC		Classification Accuracy*		True Positive Rate*	
	Training	Test	Training	Test	Training	Test
Gaussian Naïve Bayes	0.828	0.774	0.874	0.874	0.782	0.673
Logistic Regression	0.637	0.576	0.997	0.997	0.274	0.153
Decision Tree	0.997	0.503	1.000	0.992	0.995	0.010
Random Forest	0.815	0.719	0.999	0.998	0.629	0.439
Neural Network	0.789	0.704	0.998	0.998	0.579	0.408

* Classification Accuracy and True Positive Rates are calculated when all the records with a probability >= 0.5 are predicted as frauds.

5.2.2.1 Gaussian Naive Bayes

Gaussian Naive Bayes Classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions between the features. It was the most basic model we used, and was very fast to train. Accordingly, since its assumption of independence was not well satisfied, its performance was quite poor. Nine features were selected: zip_with_merchnum_7, card_amount_to_median_28, merchant_amount_to_median_28, state_with_merchnum_3,merchant_frequency_3,card_frequency_7, merchant_amount_to_avg_7, card_frequency_3, and merchant_amount_to_avg_3. This model does not suffer from overfitting as much and has high AUC scores and True Positive Rates. However, its classification accuracy is only about 87%, which is unacceptable since there are only 0.3% frauds in the dataset. This low accuracy is caused by predicting a lot of non-frauds as frauds.

5.2.2.2 Decision Tree

Decision Tree partitions the feature spaces into multiple high-dimensional boxes, and give predictions according to the majority vote in each box. A single decision tree is extremely prone to overfitting. As is shown in the summary table, although the tree selected only 2 features-merchant_amount_to_avg_28, card_amount_to_avg_14, it achieved almost perfect performance on the training set by repetitively partitioning, and performed terrible on the test set.

5.2.2.3 Logistic Regression

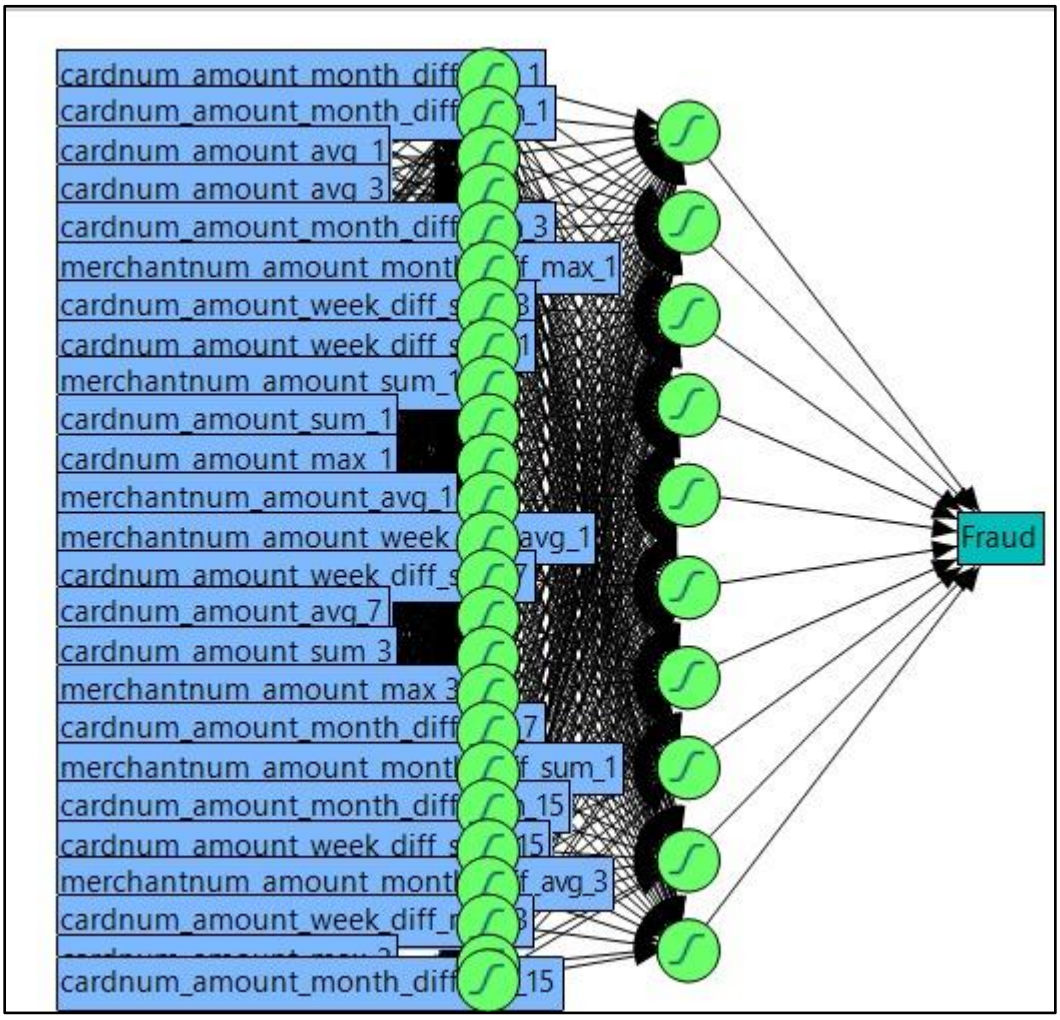
Logistic Regression model uses sigmoid function to estimate the probability, and predict probability of each record. In our case, Logistic regression selected 45 features, including zip_with_merchnum_14,card_amount_to_median_7,card_amount_to_max_3,card_amount_to_avg_28, state_with_merchnum_7, merchnum_per_card_3,etc. Although it does not suffer a lot from overfitting, its True Positive Rate is relatively low, indicating many frauds are predicted with a low probability.

Source	LogWorth	PValue
merchantnum_amount_sum_1	30.385	0.00000
cardnum_amount_sum_3	14.447	0.00000
cardnum_amount_week_diff_sum_7	10.747	0.00000
cardnum_amount_avg_3	7.463	0.00000
cardnum_amount_month_diff_avg_1	7.161	0.00000
cardnum_amount_max_1	6.968	0.00000
cardnum_amount_avg_1	5.895	0.00000
cardnum_amount_week_diff_max_3	4.894	0.00001
cardnum_amount_max_3	4.746	0.00002
merchantnum_amount_avg_1	4.666	0.00002
merchantnum_amount_week_diff_avg_1	4.134	0.00007
cardnum_amount_month_diff_sum_3	3.979	0.00010
cardnum_amount_week_diff_sum_3	3.102	0.00079
cardnum_amount_month_diff_sum_1	3.013	0.00097
cardnum_amount_month_diff_avg_15	2.841	0.00144
merchantnum_amount_month_diff_sum_1	2.736	0.00184
cardnum_amount_week_diff_sum_1	2.636	0.00231
cardnum_amount_month_diff_avg_7	2.228	0.00591
cardnum_amount_avg_7	2.027	0.00940
merchantnum_amount_max_3	1.053	0.08860
cardnum_amount_week_diff_sum_15	0.838	0.14516
cardnum_amount_month_diff_sum_15	0.749	0.17838
merchantnum_amount_month_diff_avg_3	0.575	0.26608
cardnum_amount_sum_1	0.162	0.68838
merchantnum_amount_month_diff_max_1	0.124	0.75147

Logistic Regression partitioning to evaluate the contribution of predictors on the response

5.2.2.4 Neural Network

To build a neural network classifier, we used "Multi-Layer Perceptron Classifier" in Scikit-Learn package in Python. After tuning, the parameters we used are "relu" function as the activation function, L2 penalty as 0.0001, batch size is 200, learning rate is 0.001, and 100 nodes in each hidden layer. And 3 layers are built with 13 features selected: zip_with_merchnum_14, card_amount_to_median_3,merchant_amount_to_avg_28,card_amount_to_median_14,merchant_frequency_3,card_frequency_3,merchnum_per_card_7,cardnum_per_merch_14,merchnum_per_card_3,cardnum_per_merch_28,merchant_frequency_28,merchant_amount_to_median_3,card_amount_to_max_14. The performance of Multi-Layer Perceptron Classifier is similar to random forest, and it improved on the overfitting issue.



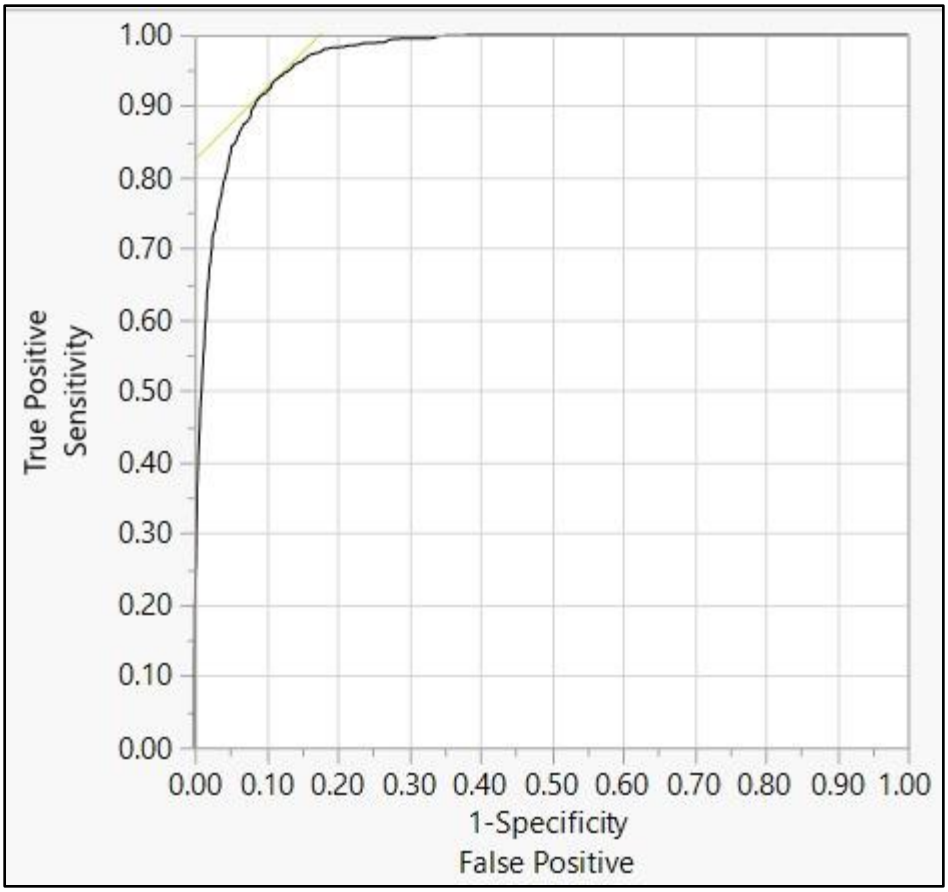
Neural Network

5.2.2.5 Random Forest

Random Forest is a modified version of decision tree, which combines multiple small trees, and considers only small amount of features at each split. Therefore, it performs far better than decision tree on the overfitting problem. It selected 9 features - zip_with_merchnum_14, merchant_amount_to_max_7,cardnum_per_merch_28,merchant_frequency_28,merchnum_per_card_28,card_frequency_3,card_amount_to_median_28,merchant_amount_to_max_28,merchant_frequency_14. And the parameters after tuning are: 25 trees, max depth of each tree is 20, and minimal sample size on each terminal node is 5. It also generated good AUC score and classification accuracy. Although the True Positive Rate was not good enough on test data, better result could be achieved by lowering the prediction threshold, such as predicting all the observations with probability >= 0.3 as frauds.

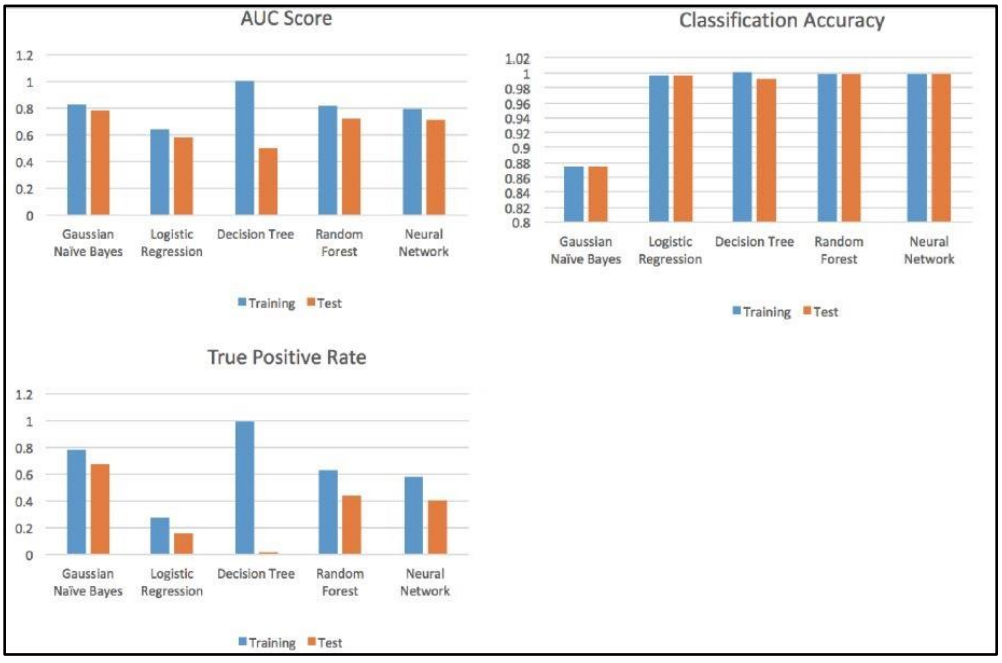
	Fraud		
Predictor	Contribution	Portion	Rank
cardnum_amount_month_diff_sum_3	47.1125	0.1676	1
cardnum_amount_sum_3	30.3670	0.1080	2
cardnum_amount_sum_1	30.1621	0.1073	3
cardnum_amount_week_diff_sum_1	28.3481	0.1009	4
cardnum_amount_week_diff_sum_3	28.0321	0.0997	5
cardnum_amount_month_diff_sum_1	16.7704	0.0597	6
merchantnum_amount_sum_1	13.6179	0.0484	7
merchantnum_amount_month_diff_sum_1	13.0390	0.0464	8
cardnum_amount_max_3	10.8681	0.0387	9
cardnum_amount_week_diff_sum_7	7.1813	0.0255	10
cardnum_amount_week_diff_max_3	5.7419	0.0204	11
cardnum_amount_month_diff_sum_15	4.9791	0.0177	12
merchantnum_amount_month_diff_max_1	4.8036	0.0171	13
merchantnum_amount_avg_1	4.6146	0.0164	14
cardnum_amount_max_1	4.3300	0.0154	15
cardnum_amount_avg_3	4.1590	0.0148	16
cardnum_amount_avg_1	4.1219	0.0147	17
merchantnum_amount_max_3	3.8105	0.0136	18
merchantnum_amount_month_diff_avg_3	3.7181	0.0132	19
merchantnum_amount_week_diff_avg_1	3.6167	0.0129	20
cardnum_amount_week_diff_sum_15	3.1844	0.0113	21
cardnum_amount_month_diff_avg_15	2.8551	0.0102	22
cardnum_amount_month_diff_avg_1	2.6148	0.0093	23
cardnum_amount_avg_7	1.9606	0.0070	24
cardnum_amount_month_diff_avg_7	1.0637	0.0038	25

Bootstrap forest partitioning to evaluate the contribution of predictors on the response



ROC Plot for Random Forest : 97.128% Area under curve

5.2.3 Summary



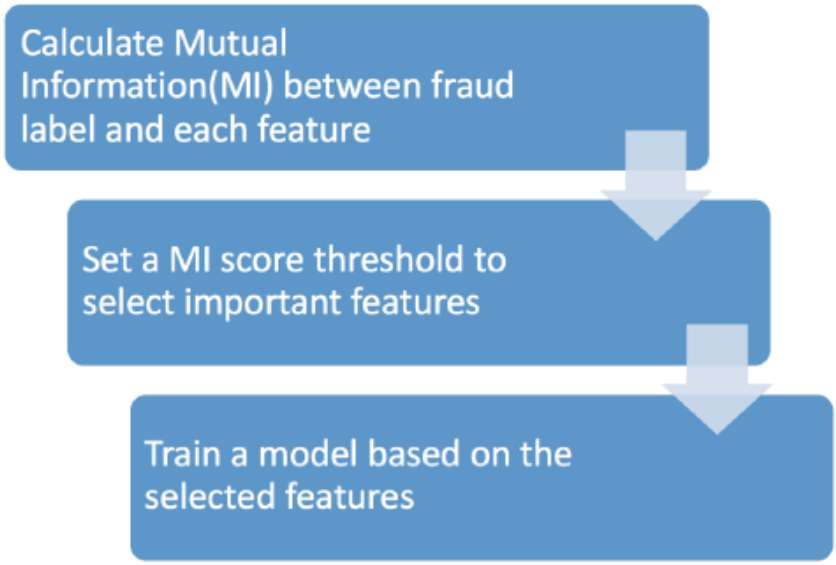
According to the above analysis and comparison, our conclusions are: Decision Tree model suffers a lot from overfitting; Gaussian Naive Bayes model has poor classification accuracy, predicting lots of non-frauds as fraud; Logistic Regression model do not overfit much, but both cannot capture enough frauds; Random Forest and Neural Network models are the best performing models among all the six models.

	Gaussian Naïve Bayes	Logistic Regression	Random Forest	Neural Network
1	zip_with_merchnum_7	zip_with_merchnum_14	zip_with_merchnum_14	zip_with_merchnum_14
2	card_amount_to_median_28	card_amount_to_median_7	merchant_amount_to_max_7	card_amount_to_median_3
3	merchant_amount_to_median_28	card_amount_to_max_3	cardnum_per_merch_28	merchant_amount_to_avg_28
4	state_with_merchnum_3	card_amount_to_avg_28	merchant_frequency_28	card_amount_to_median_14
5	merchant_frequency_3	state_with_merchnum_7	merchnum_per_card_28	merchant_frequency_3
6	card_frequency_7	merchnum_per_card_3	card_frequency_3	card_frequency_3
7	merchant_amount_to_avg_7	merchnum_per_card_28	card_amount_to_median_28	merchnum_per_card_7
8	card_frequency_3	card_amount_to_max_7	merchant_amount_to_max_28	cardnum_per_merch_14
9	merchant_amount_to_avg_3	card_amount_to_avg_3	merchant_frequency_14	merchnum_per_card_3
10		merchant_amount_to_avg_3		cardnum_per_merch_28

Type I variable
Type II variable
Type III variable
Type IV variable

When we look at the top 10 selected variables (the 10 variables that are first selected) for each model, a noticeable pattern is that all the models selected type III variable - the number of different zip code related to a particular merchant number - at the very beginning, indicating that geographical pattern is a very useful feature to detect frauds. Besides, all the models selected several type I variables, since unusual transaction patterns can also play a key role in detecting frauds. Some of the Type II and Type IV variables were also selected as top 10 variables, but generally speaking, they are not as important as the other two types of variables.

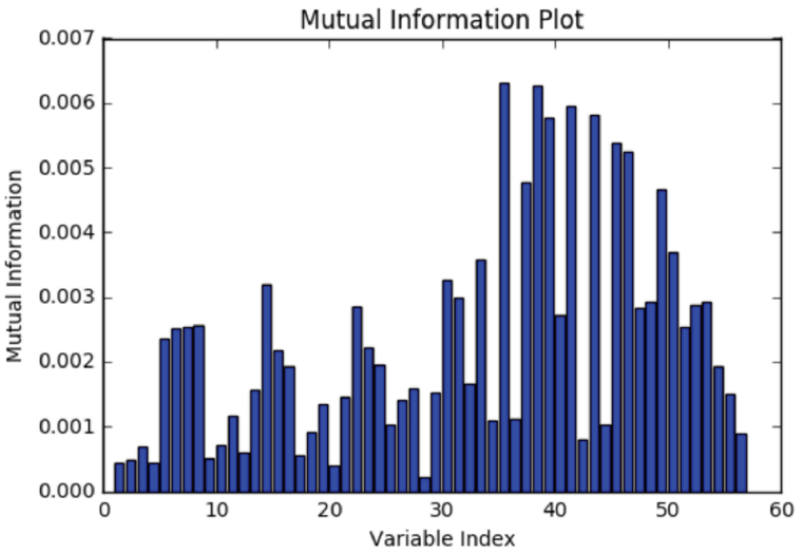
5.3 Feature Selection Based on Mutual Information



We have also tried to select features based on Mutual Information score, and trained models only on the selected important features. Mutual Information criterion was applied to select significant features in fraud analysis.

This Mutual Information (MI) method measured the mutual dependence between each variable we built and the dependent variable 'fraud'. More specifically, it quantified the 'amount of information' obtained from each variable through the variable 'fraud' and gave a score. It is equal to zero if and only if two random variables are independent, and higher values mean higher dependency.

Before calculating the mutual information, we first z-scaled all the features to get rid of the influence of different units. Then we used the "mutual_info_classif" function in the Scikit-Learn package in Python to calculate the mutual information score. The mutual information calculated are shown in the graph below.



As we can see from the graph, about one-fourth of the mutual information scores are higher than 0.003. To be precise, 13 out of 56 mutual information are higher than 0.003, 9 out of 56 mutual information are higher than 0.004, and 7 out of 58 mutual information are higher than 0.005. To avoid overfitting by involving too many variables, we decided to set the threshold at 0.004. Therefore, the 9 features we selected were:

Expert Variable	Mutual Information
zip_with_merchnum_7	0.0063
cardnum_per_merch_7	0.0063
zip_with_merchnum_14	0.0060
zip_with_merchnum_28	0.0058
merchnum_per_card_3	0.0058
cardnum_per_merch_14	0.0054
cardnum_per_merch_28	0.0052
cardnum_per_merch_3	0.0048
merchant_frequency_3	0.0047

The performance of models trained with these features are shown as below. We can see the performance is not better than the features selected through forward selection method. This could be due to the fact that, when we select features based on mutual information, we only considered the dependency between each feature and fraud, but did not take into consideration the effect of combining features. For example, we selected three type III variables - zip_with_merchnum_7,zip_with_merchnum_14,zip_with_merchnum_28, but the information they provided could be highly overlapped. Besides, some features could work much better when they are used together.

5.4 Conclusion of the Algorithms

To conclude, we have tried two feature selection methods: wrapped forward stepwise feature selection and filter feature selection method based on mutual information. Forward stepwise feature selection gives us better classification results than feature selection based on mutual information. To strike a balance between prediction accuracy and overfitting, we think the best models are Random Forest Model and Neural Network Model with features selected by the forward feature selection.

6. Results

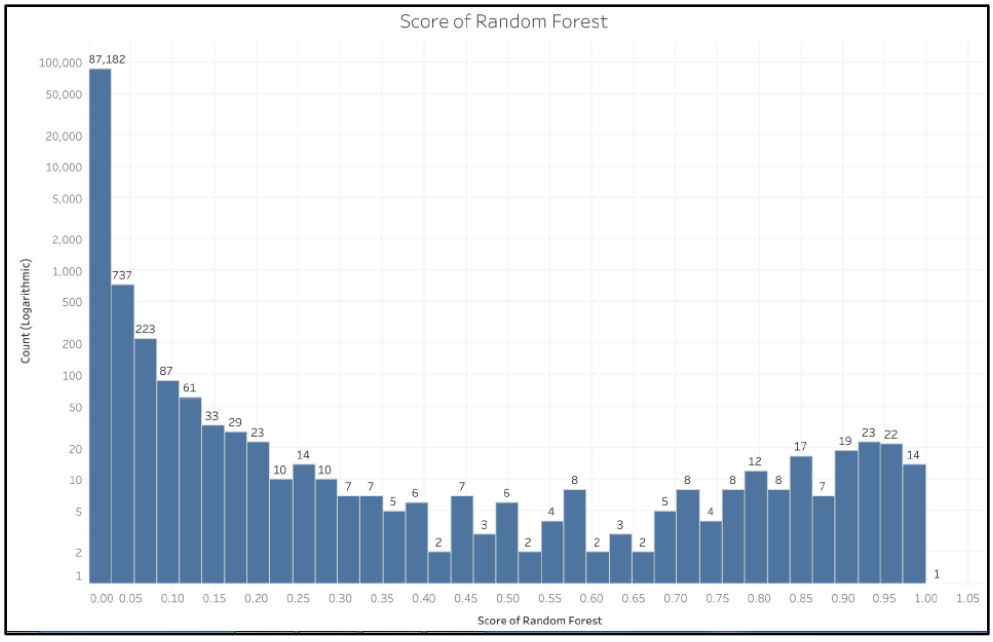
As analyzed above, we found that the models built using forward stepwise feature selection have better performance than those built using features selected based on mutual information. In the following part, we will go through the fraud detection results from Gaussian Naive Bayes Model, Logistic Regression Model, Random Forest Model, and Neural Network Model with forward stepwise feature selection method. Here we ignore Decision Tree Model, since it overfitted too much. After that, we will also show the result of ensemble modeling methods, which calculate fraud score by averaging the scores of Neural Network and Random Forest or pick the maximum score between Neural Network and Random Forest scores.

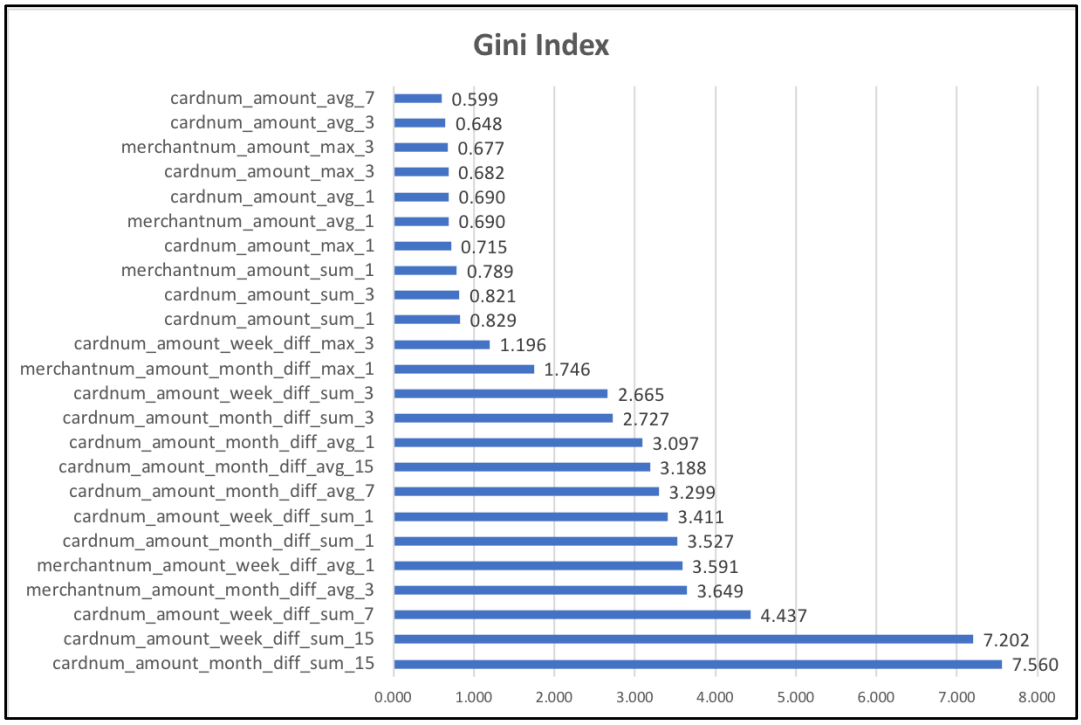
	Bootstrap Forest (150 trees)	Boosted Trees	Neural Network	Naive Bayes	Logistic Regression
Training	71.51%	70.41%	77.89%	65.98%	62.13%
Testing	58.94%	53.61%	60.08%	38.78%	49.05%
OOT	52.37%	51.48%	42.31%	50.00%	47.63%

FDR at 2% for Different Models

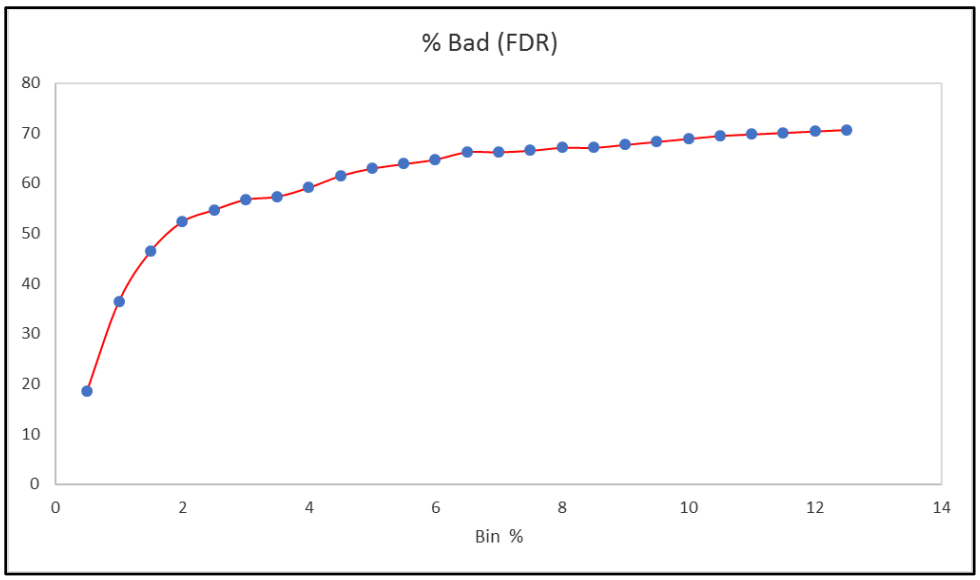
6.1 Results of Best Model

Random Forest: For this case, Random Forest outperformed the other algorithms that we tried. The below diagram shows the histogram of fraud scores from Random Forest. The fraud scores are scattered from 0 to 1 and there is a good amount of fraud scores on right i.e. records which are flagged as fraud. We used logarithmic scale on y-axis for clarity.





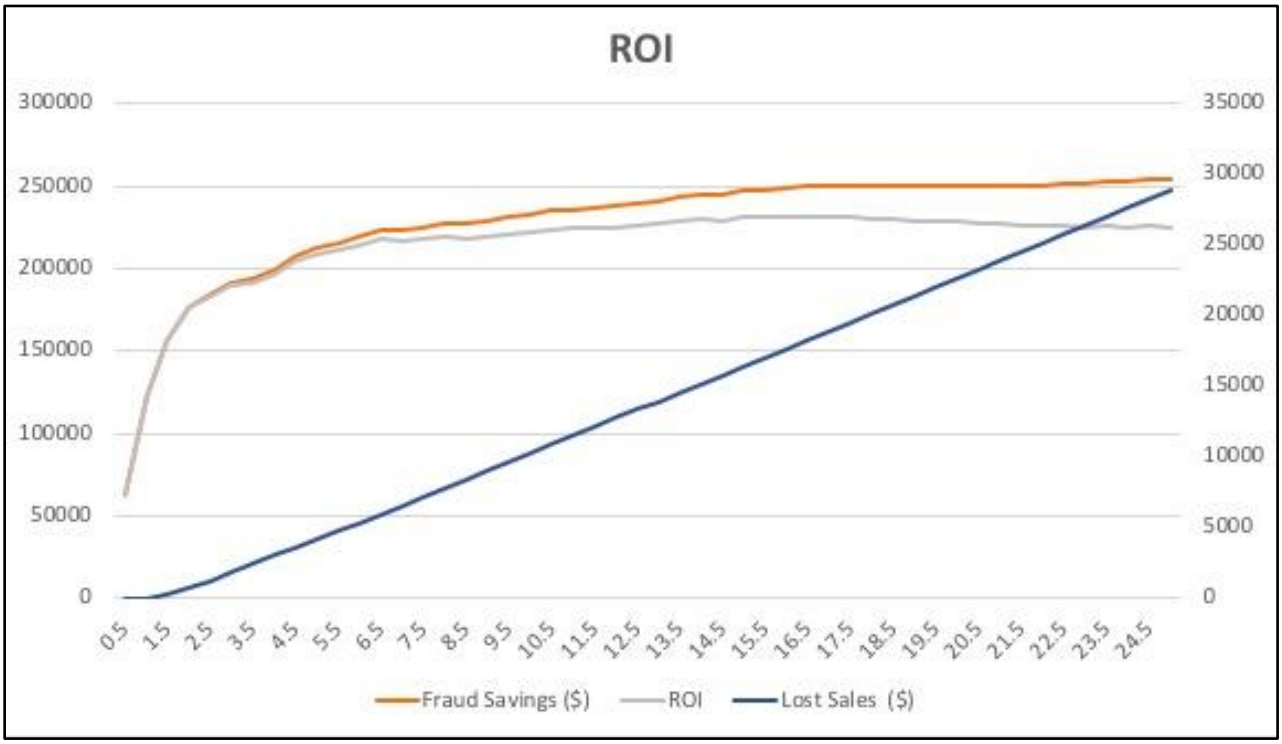
Overall Bad Rate is 2.69%	Bin Statistics					Cumulative Statistics					
Population Bin %	Total # records	# Bad	# Good	% Bad	% Good	Cumulative Bad	Cumulative Good	% Bad (FDR)	% Good	KS	False Pos. Ratio
0.5	63	63	0	100	0	63	0	18.6390533	0	18.6390533	0
1	63	60	3	95.2380952	4.76190476	123	3	36.3905325	0.02449379	36.3660387	0.02439024
1.5	63	34	29	53.968254	46.031746	157	32	46.4497041	0.26126715	46.188437	0.20382166
2	63	20	43	31.7460317	68.2539683	177	75	52.3668639	0.61234487	51.754519	0.42372881
2.5	63	8	55	12.6984127	87.3015873	185	130	54.7337278	1.06139778	53.67233	0.7027027
3	63	7	56	11.1111111	88.8888889	192	186	56.8047337	1.51861528	55.2861184	0.96875
3.5	63	2	61	3.17460317	96.8253968	194	247	57.3964497	2.01665578	55.3797939	1.27319588
4	63	6	57	9.52380952	90.4761905	200	304	59.1715976	2.48203788	56.6895597	1.52
4.5	63	8	55	12.6984127	87.3015873	208	359	61.5384615	2.93109079	58.6073707	1.72596154
5	63	5	58	7.93650794	92.0634921	213	417	63.0177515	3.40463749	59.613114	1.95774648
5.5	63	3	60	4.76190476	95.2380952	216	477	63.9053254	3.89451339	60.0108121	2.20833333
6	63	3	60	4.76190476	95.2380952	219	537	64.7928994	4.38438929	60.4085101	2.45205479
6.5	63	5	58	7.93650794	92.0634921	224	595	66.2721893	4.85793599	61.4142534	2.65625
7	63	0	63	0	100	224	658	66.2721893	5.37230568	60.8998837	2.9375
7.5	63	1	62	1.58730159	98.4126984	225	720	66.5680473	5.87851078	60.6895366	3.2
8	63	2	61	3.17460317	96.8253968	227	781	67.1597633	6.37655127	60.783212	3.44052863
8.5	63	0	63	0	100	227	844	67.1597633	6.89092097	60.2688423	3.71806167
9	63	2	61	3.17460317	96.8253968	229	905	67.7514793	7.38896146	60.3625178	3.95196507
9.5	63	2	61	3.17460317	96.8253968	231	966	68.3431953	7.88700196	60.4561933	4.18181818
10	63	2	61	3.17460317	96.8253968	233	1027	68.9349112	8.38504246	60.5498688	4.40772532
10.5	63	2	61	3.17460317	96.8253968	235	1088	69.5266272	8.88308295	60.6435443	4.62978723
11	63	1	62	1.58730159	98.4126984	236	1150	69.8224852	9.38928805	60.4331972	4.87288136
11.5	63	1	62	1.58730159	98.4126984	237	1212	70.1183432	9.89549314	60.2228501	5.11392405
12	63	1	62	1.58730159	98.4126984	238	1274	70.4142012	10.4016982	60.0125029	5.35294118
12.5	63	1	62	1.58730159	98.4126984	239	1336	70.7100592	10.9079033	59.8021558	5.58995816



The plot below demonstrates the business values of Random Forest Model.

Assumptions :

- $1000 loss for every fraud that's not caught.
- $10 loss for every false positive (good that's flagged as a bad)
- Cutoff point should be 16.5% because beyond that the ROI becomes flat.



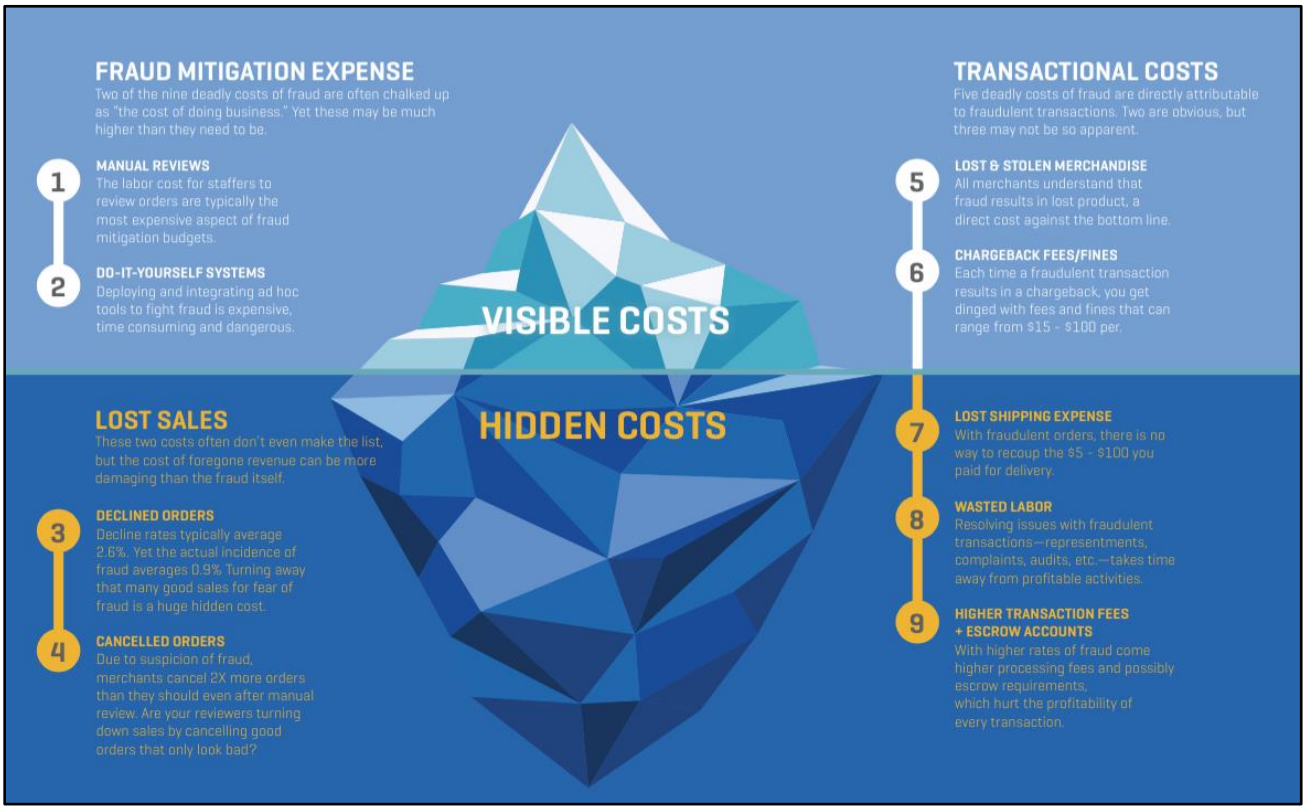
6.2 Conclusion

From comparing all the models and their performances, we could decide that Random Forest Model with the 9 variables selected during the forward feature selection process performed best.
And to generate most business value, i.e. ROI, we should flag all the records with top scores as frauds. The estimated ROI using the given dataset is $231,710.

Population Bin(%)	Fraud Savings ($)	Lost Sales ($)	ROI
0.5	63000	0	63000
1	123000	30	122970
1.5	157000	320	156680
2	177000	750	176250
2.5	185000	1300	183700
3	192000	1860	190140
3.5	194000	2470	191530
4	200000	3040	196960
4.5	208000	3590	204410
5	213000	4170	208830
5.5	216000	4770	211230
6	219000	5370	213630
6.5	224000	5950	218050
7	224000	6580	217420
7.5	225000	7200	217800
8	227000	7810	219190
8.5	227000	8440	218560
9	229000	9050	219950
9.5	231000	9660	221340
10	233000	10270	222730
10.5	235000	10880	224120
11	236000	11500	224500
11.5	237000	12120	224880

12	238000	12740	225260
12.5	239000	13360	225640
13	241000	13970	227030
13.5	243000	14580	228420
14	245000	15190	229810
14.5	245000	15820	229180
15	248000	16420	231580
15.5	248000	17050	230950
16	249000	17670	231330
16.5	**250000**	**18290**	**231710**
17	250000	18920	231080
17.5	251000	19540	231460
18	251000	20170	230830
18.5	251000	20800	230200
19	251000	21430	229570
19.5	251000	22060	228940
20	251000	22690	228310
20.5	251000	23320	227680
21	251000	23950	227050
21.5	251000	24580	226420
22	251000	25210	225790
22.5	252000	25830	226170
23	252000	26460	225540
23.5	253000	27080	225920
24	253000	27710	225290
24.5	254000	28330	225670
25	254000	28960	225040
		max ROI	**231710**

6.3 Business Insights and Real-World Scenario



Appendix

Data Quality Report

Dataset: Card Transaction Data

Description: This data is a simulated representation of the 96708 card transaction details applications during 2010. A typical observation contains information about the card and merchant details, along with geographical location parameters and dollar amount transacted.

Number of Records: 96708

Number of Variables: 10

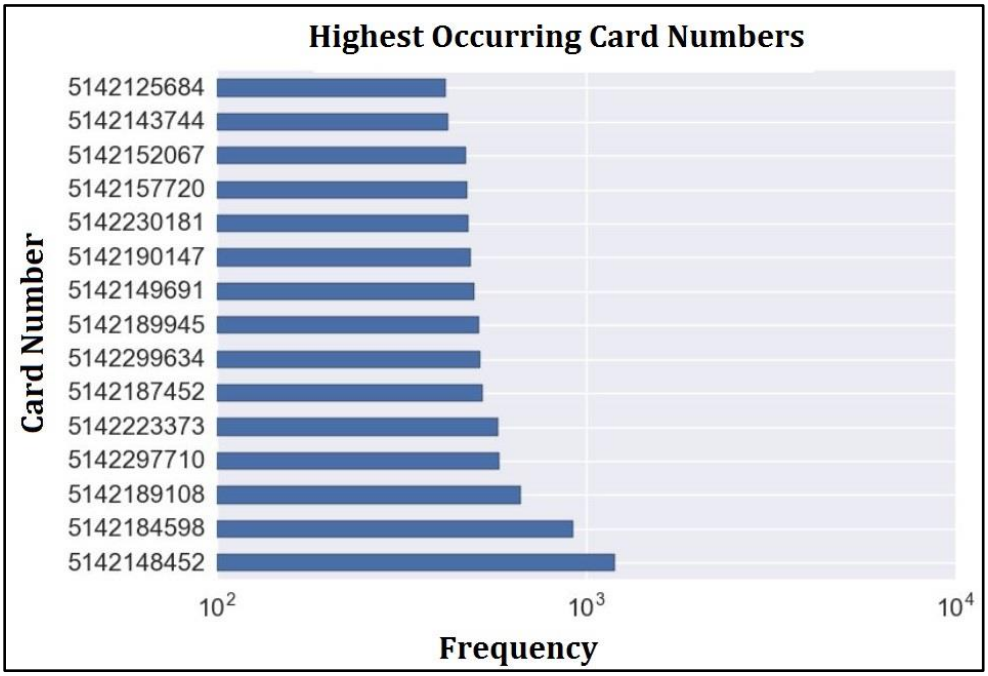
Summary statistics for numerical variables

Variable	Description	Percentage Populated	Unique Values	Most Common Occurance	Mode
Cardnum	Card Number	100%	1644	5142148452	1192
Date	Date	100%	365	2/28/2010	684
Merchantnum	Merchant ID Number	96.51%	13090	930090121224	9310
Merch Description	Merchant Description	100%	13125	GSA-FSS-ADV	1688
Merchant State	Merchant State	98.76%	227	TN	11990
Merchant Zip	Merchant Zipcode	95.18%	4567	38118	11823
Transtype	Transaction Type	100%	4	P	96353
Amount	Amount	100%	34876	$3.62	4283
Fraud	Fraud (Yes/No)	100%	2	0	95694

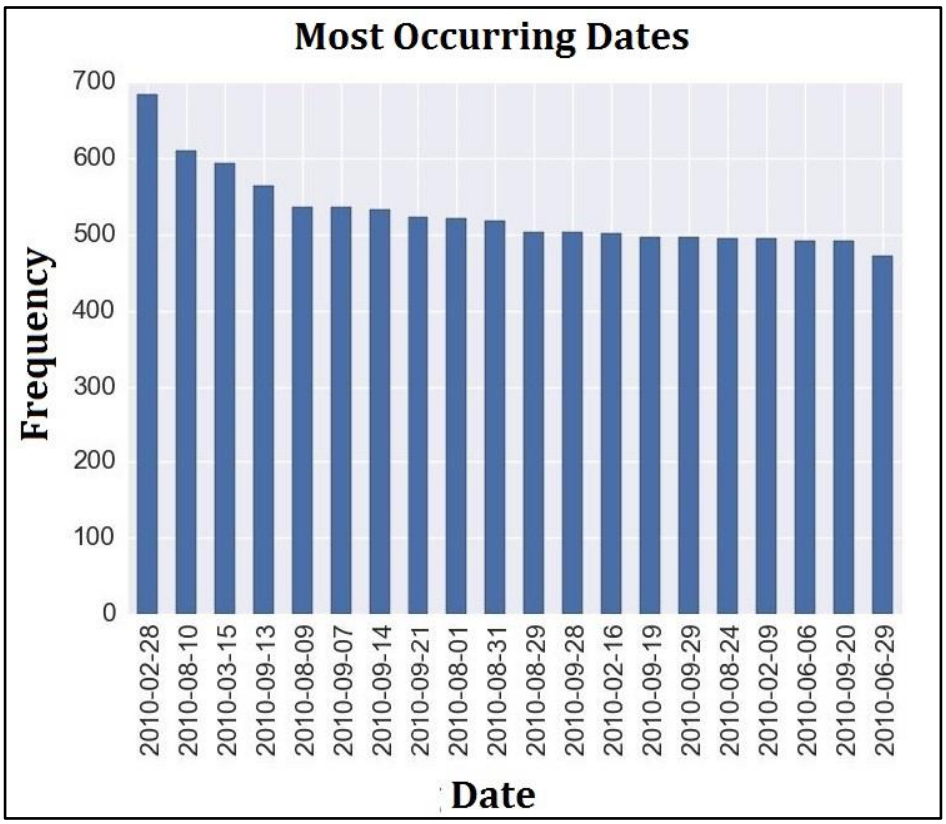
Description and visualization of data

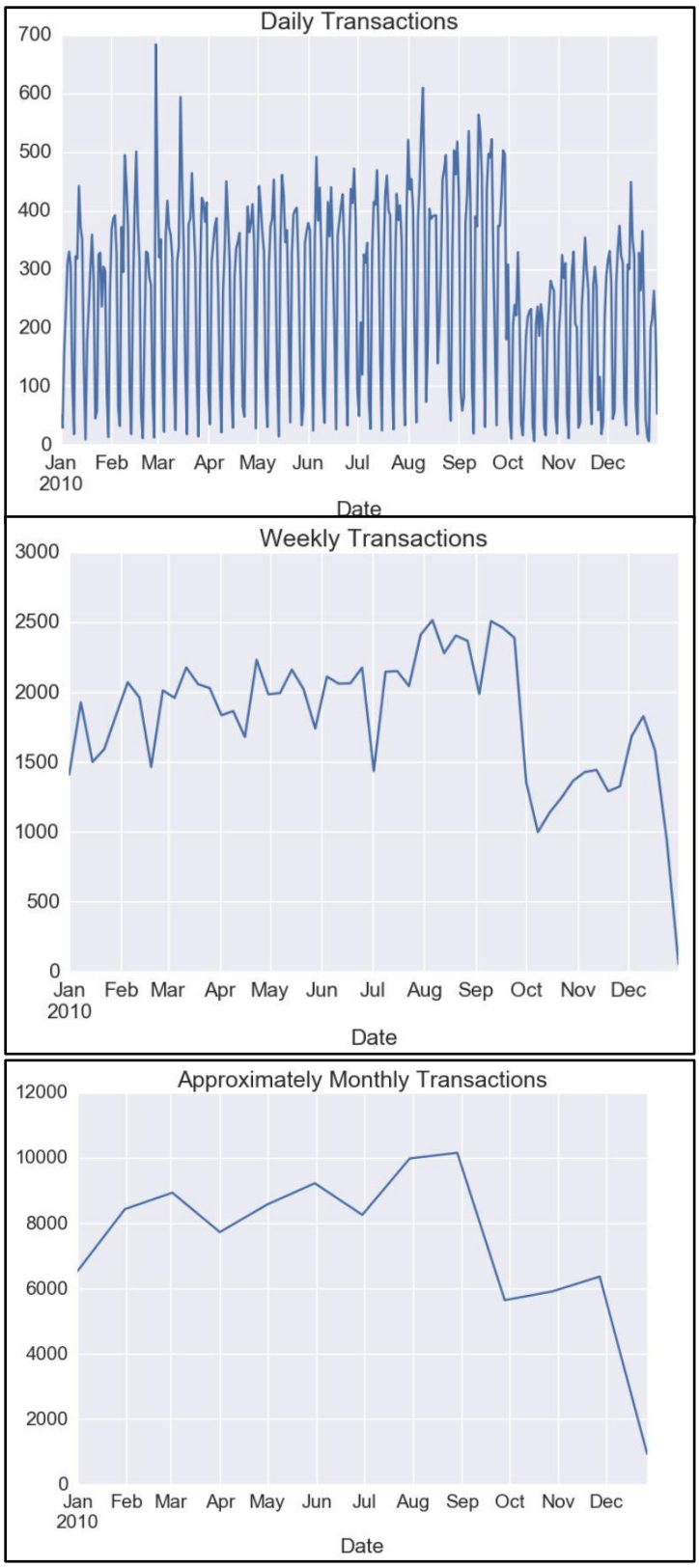
1. *Recordnum* is a categorical variable. It works as the ordinal reference number for each property record. There are 96708 records overall. Each row is a unique number/identifier and hence, a visualization is not required.

2. *Cardnum* refers to the Card Number used to make transaction.

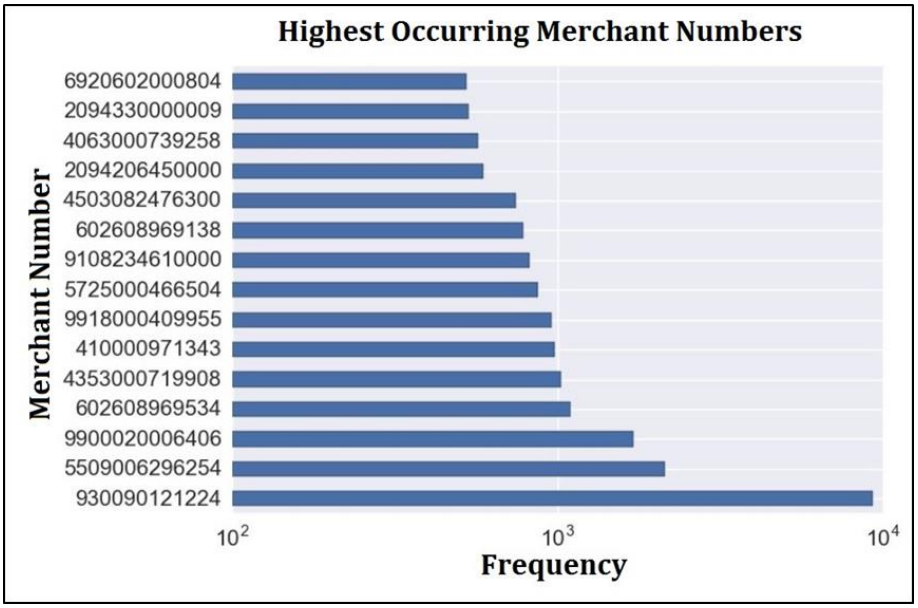


3. *Date* refers to the date on which the transaction was made.

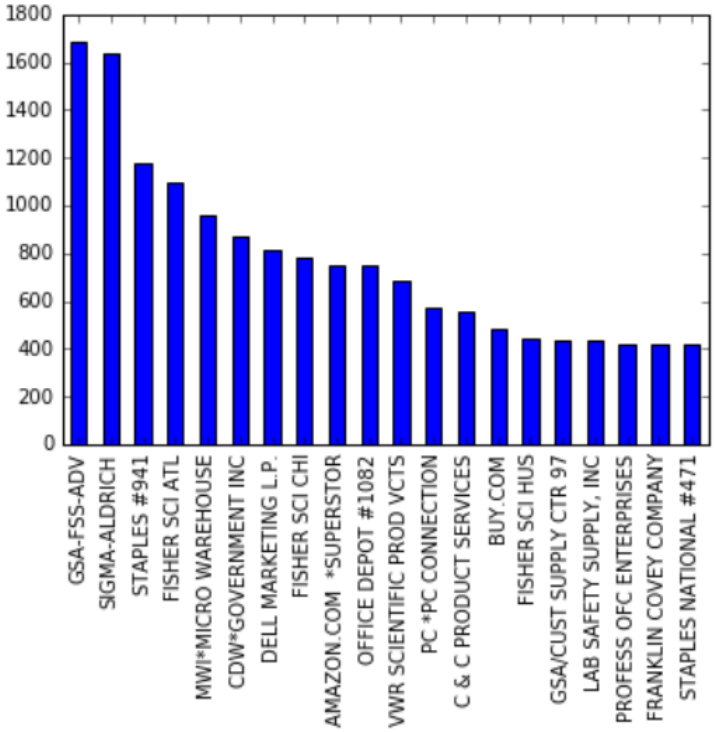




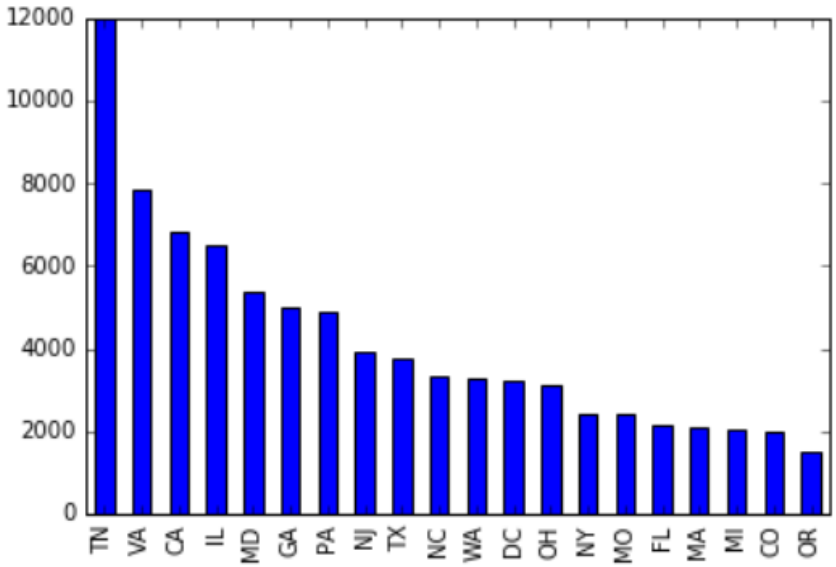
4. ***MerchantNum*** refers to unique Merchant ID associated with each transaction.



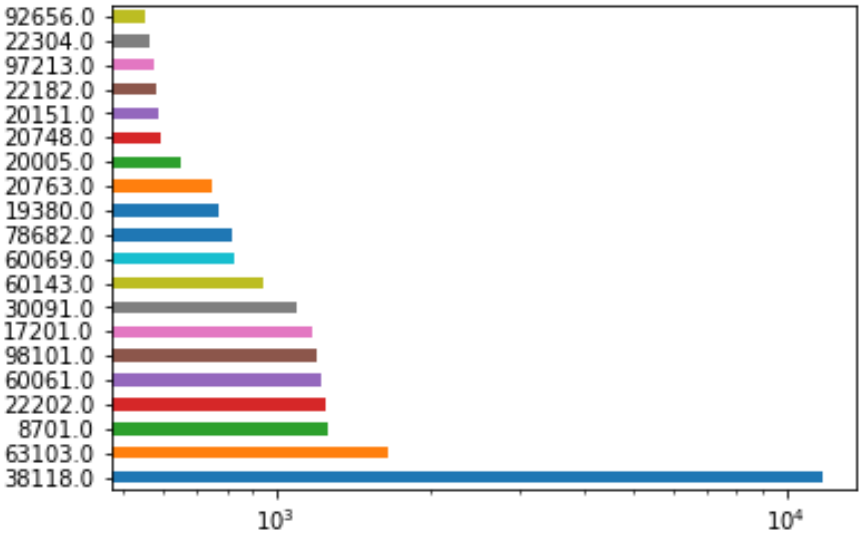
5. ***Merch Description*** refers to the name of the merchant which carried out the transaction. 20 most frequently occurring merchants have been shown below.



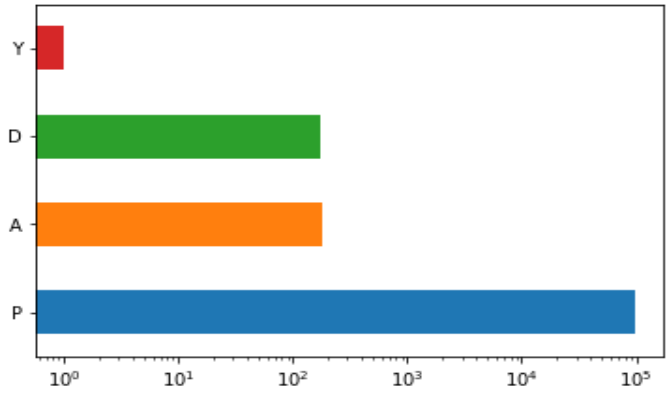
6. ***Merchant State*** refers to the state in which the merchant is located. States are abbreviated using 2-letter codes.



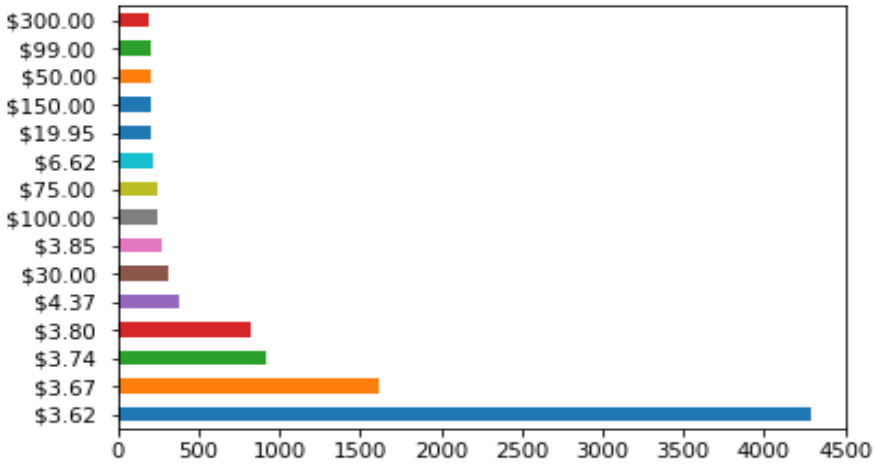
7. ***Merchant Zip*** contains information about each merchant's ZIP code. Below is a graph of the top 20 most frequent zip codes.



8. ***Transtype*** is a categorical variable referring to the type of transaction. There are four different types of transactions in the dataset with no missing values.



9. ***Amount*** contains information about the dollar amount corresponding to each transaction. Below is a graph of the top 15 most frequent transaction amounts.



10. ***Fraud*** contains information whether observation includes fraudulent data or not. Of the total 96,708 observations, we observed that 95,694 observations were noted as accurate/legitimate, while 1,014 observations were marked as fraudulent.

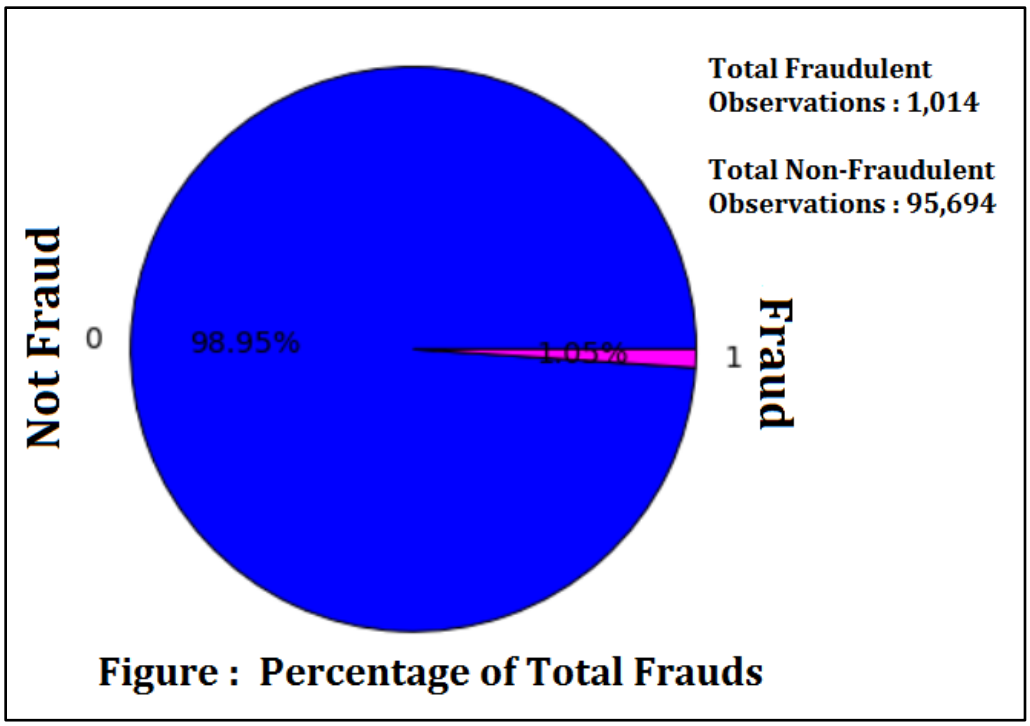


Figure : Percentage of Total Frauds

Summary

The Data Quality Report created for the Card Transaction dataset is required for the integrity of the data management by covering gaps of data issues. We not only cleaned and transformed the data, but also rectified inconsistencies and redundancies. Furthermore, we tabulated and visualized all variables, which provided us new insights into the dataset. These reports are valuable when administered on data that has made multiple iterations and additions before that data becomes authorized or stored for enterprise intelligence. As we gather more data to add to our current database, we can construct similar accuracy checks for all data sourced to our class project.

Future Scope

This report will aid data governance by monitoring data to find exceptions and anomalies undiscovered by previous data management operations. Further data quality checks may be defined at attribute level to have full control on its remediation steps. This report will serve as a cornerstone for all future phases of the group project.