Fraud Analytics Project 2 – Supervised Fraud Algorithm on Card Transaction

Team 5

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2. Executive Summary:

Credit card transactions are always filled with frauds, and this is a severe problem that has been harassing banks for decades. Usually, credit card issuing banks compensate the fail-to-identify illegitimate transaction for their customers, causing banks huge expenses and dramatically lowering their profitability. Given this situation, this project is aimed to provide a machine-learning-based and real-time system to detect fraudulent transactions and testify the profitability of this system.

We collected transaction data, cleaned messy fields, created new variables, and built models using selected variables to predict fraudulent transactions. Comparing the average FDR(Fraud Detection Rate) at 3% of each model, we locate the best-performed model and name it as our solution to this credit card fraud detection problem. Derived from our calculation on assumption, this model is proven to be cost-effective and time-saving as it saves $226800 by checking only 6% of 12427 OOT transactions.

3. Description of Data:

Dataset Name: Card Transactions Data Explore
Detailed Description: This dataset records the card transaction data of a certain bank for the purpose to dig out the fraud transaction's features, as well as the exact approach to pick out them. It includes all the transactions for the whole year of 2010.
Date: 1/1/2010 - 12/31/2010
Number of Fields: 10
Number of Records: 96,753

In this section, the overview of raw data is presented.

Fields overview:

	colname	type	count	populated (%)	# zero	# unique
1	Recnum	int64	96753	1	0	96753
2	Cardnum	category	96753	1	0	1645
3	Date	datetime64	96753	0.97	0	365
4	Merchnum	category	93378	1	231	13091
5	Merch description	category	96753	0.99	0	13126
6	Merch state	category	95558	1	0	227
7	Merch zip	int64	96753	1	0	4568
8	Transtype	category	96753	1	0	4
9	Amount	float64	96753	1	0	34909
10	Fraud	category	96753	0	95694	2

Date fields:

colname	count	unique	top	freq	first	last
Date	96753	365	2010-02-28	684	2010-01-01	2010-12-31

Numeric fields:

colname	count	mean	std	min	25%	50%	75%	max
Recnum	96753	48377.00	27930.33	1	24189	48377	72565	96753
Amount	96753	427.89	10006.14	0.01	33.48	137.98	428.2	3102045.53

*Recnum is not an actual numeric field since it is an index.

Categorical fields:

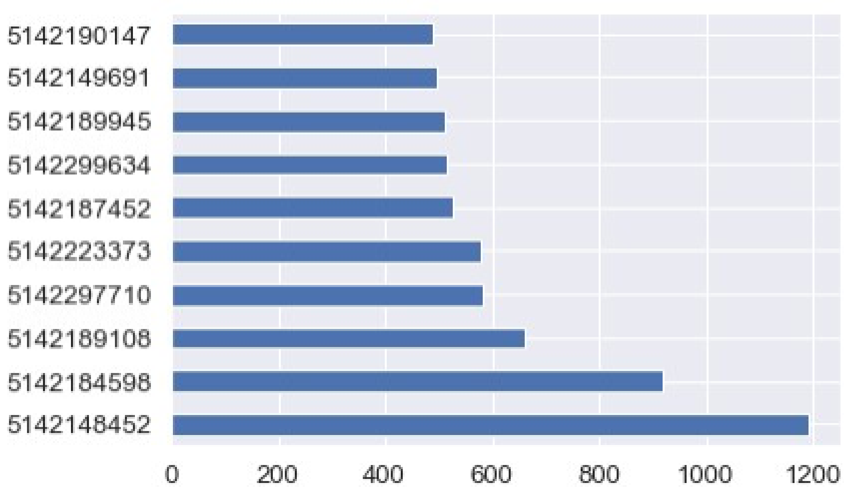
colname	count	unique	top	freq
Cardnum	96753	1645	5142148452	1192
Merchnum	93378	13091	9.3009E+11	9310
Merch description	96753	13126	GSA-FSS-ADV	1688
Merch state	95558	227	TN	12035
Merch zip	96753	4568	38118	11868
Transtype	96753	4	P	96398
Fraud	96753	2	0	95694

Description of the Columns in the Data

In this section, we introduce the meaning of each column, see the distribution of these numeric fields and frequently occurring values of categorical fields.

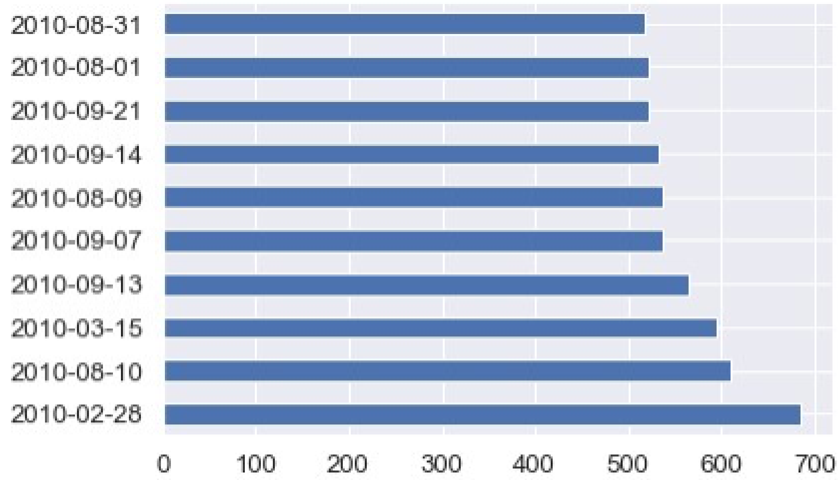
1. **Recnum:** The index of records

2. **Cardnum:** Card number

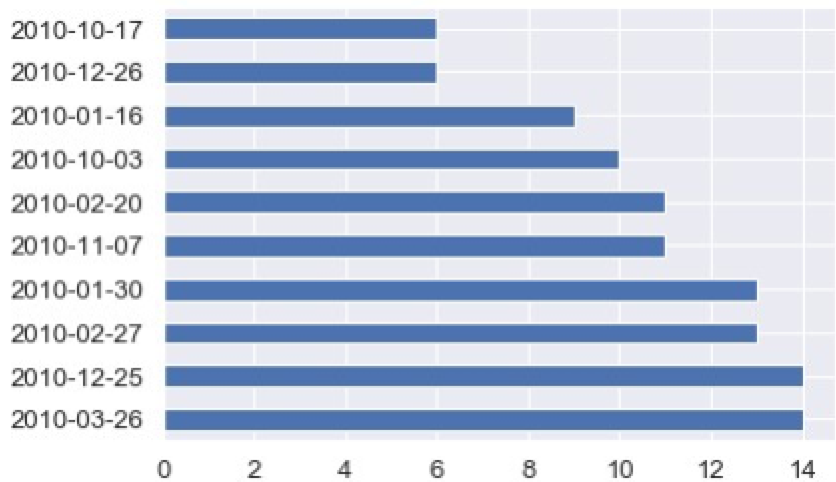


Top 10 Most Frequent Cardnum

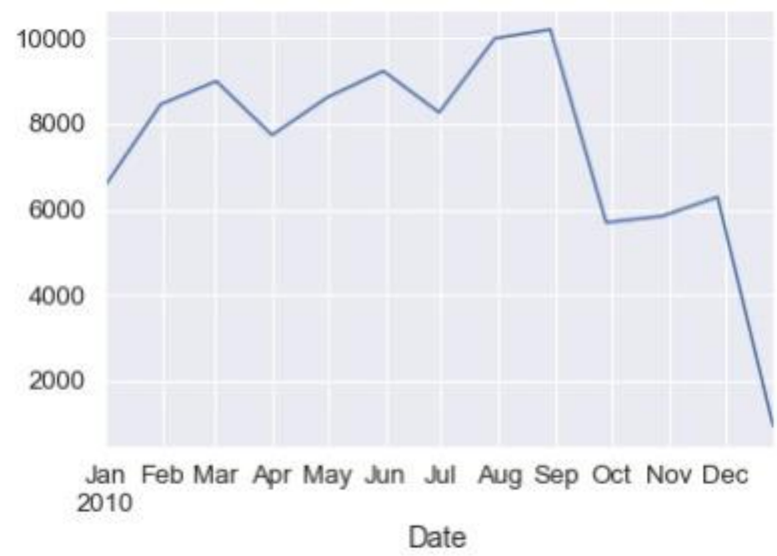
3. Date: Transaction Date (YYYY-mm-dd)



Top 10 Most Frequent Date

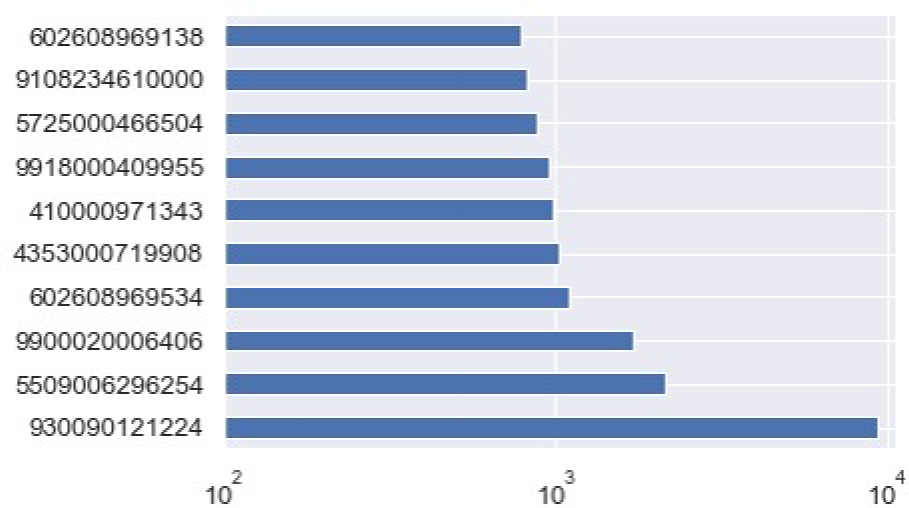


Top 10 Least Frequent Date



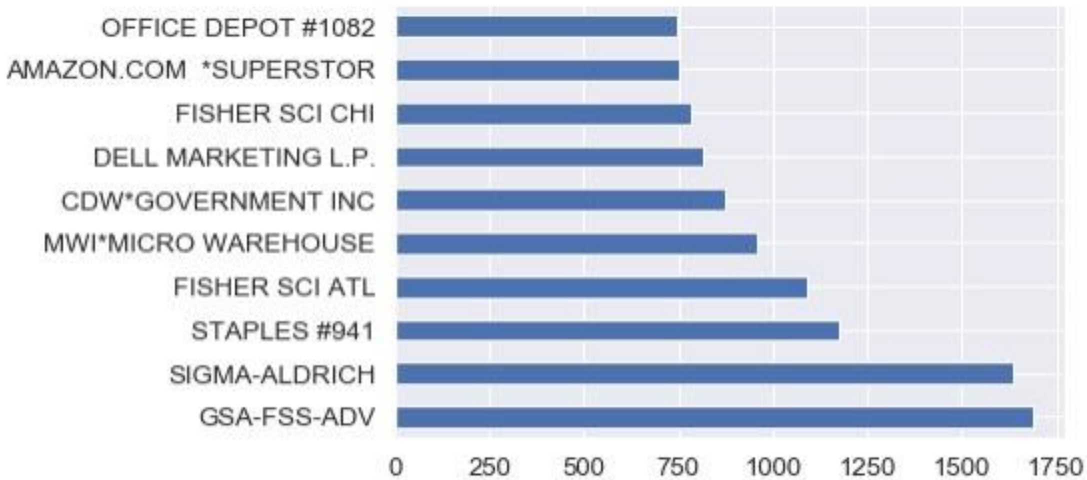
Monthly transactions

4. Merchnum: Identifier of each merchant



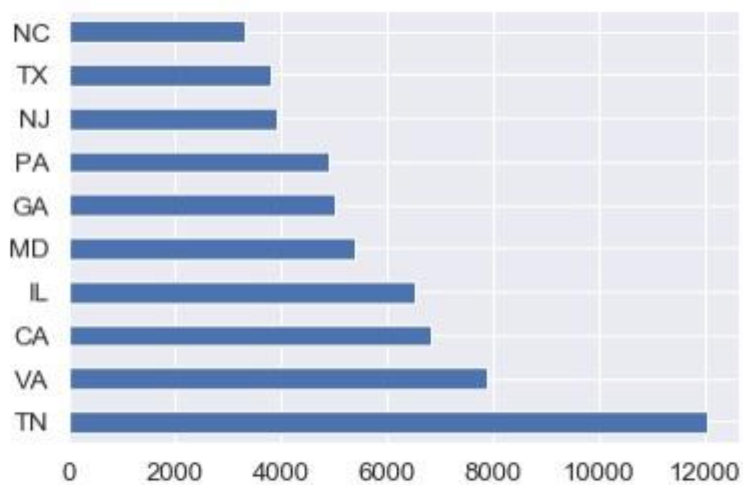
Top 10 Most Frequent Merchnum

5. Merch description: Brief description of each merchant



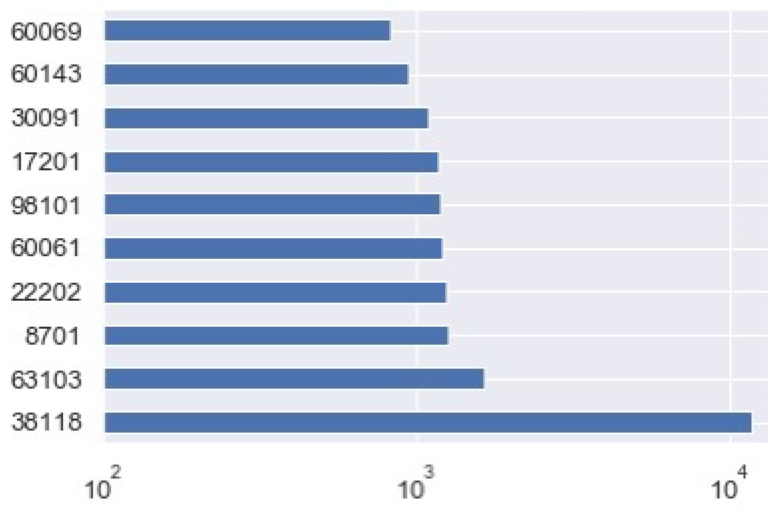
Top 10 Most Frequent Merch description

6. Merch state: State abbreviation of each merchant



Top 10 Most Frequent Merch state

7. Merch zip: 5-digit zip code of each merchant.

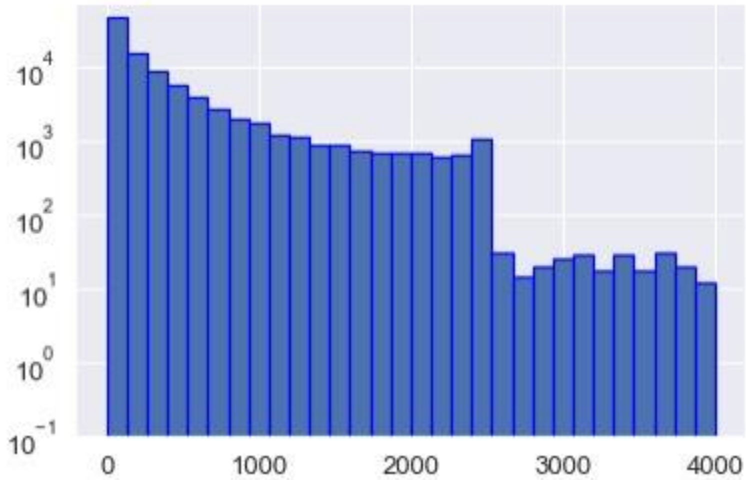


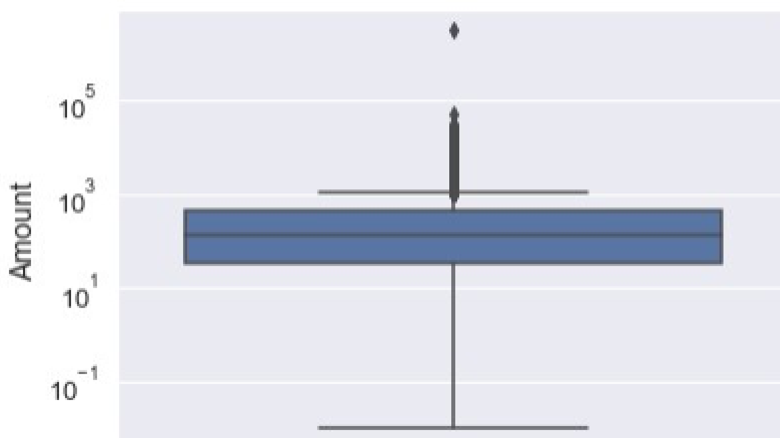
Top 10 Most Frequent Merch zip

8. Transtype: Transaction type.

Type	Description	Count
P	Prenote, refers to a prenotification payment	96398
A	Authorization, refers to a request to charge a cardholder	181
D	Delayed Capture, refers to a capture mark the funds set asideby an approved Authorization transaction for capture during the next settlement period.	173
Y	Don't know	1

9. Amount: Amount of transactions





10. Fraud: Whether this transaction is fraudulent (0 represents a normal transaction, 1 denotes fraud).

Fraud	Count
0	95694
1	1059

4. Data Cleaning:

This section covers the data cleaning steps we followed to removing the irrelevant categories or unreliable outliers and filling in the missing values under significant fields. We first choose the Transtype equals “P” in the data set and omit the merchant Amount over 100000, because it has little relation to the fraud behaviour.

Merchnum: We first aggregate merchant numbers by merchant description and fill in the most common merchant number for each merchant description. Then we aggregate it by merchant zip and fill in the mode of merchant number for each merchant zip code, and aggregate it by merchant state and fill in the most common merchant number for each merchant state if there are still zero values. In the end, we fill the rest using random numbers.

Merch state: To commence, there are some three digital numbers in the State, we first change them to its corresponding state and aggregate merchant state by merchant zip code and fill in the most common merchant state for each zip code. Then, we aggregate by merchant number and fill the most common merchant state for each merchant number. Based on the merchant description, we process the similar steps again and fill the rest with cardnum and “TN”, which is the most frequent states.

Merch Zip: we first group merchant zip by merchant number and merchant state at the same time and fill in the most common merchant zip for each merchant number and merchant state. Later, we then group it by merchant description and merchant state, together, and fill in the mode of merchant zip for each merchant description and merchant state. And we group it by merchant description and merchant state, together, and fill in the mode of merchant zip for each merchant description and merchant state. After filling it by the merchant state group or merchant description, we fill the rest with “unknown”.

5. Candidate Variables:

Given that frequency and amount of transactions are different from regular ones, target encoding is an excellent approach to transform all the current fields into numeric variables related to each categorical entity to represent the pattern of transactions, the idea is to build a table with values for each category in the train set by smoothing formula.

Amount Variables: We calculate the average, maximum, median, total, actual average, actual maximum, actual median, actual total amount separately by card, merchant, card at this merchant, card in this zip code, card in this state over the past 0,1,3,7,14,30 days. The total is 240 variables.

Frequency Variables: We calculate the number of transactions with this card, merchant, card at this merchant, card in this zip code, card in this state over the past 0, 1, 3, 7, 14, 30 days, and 5 new variables are created.

Days-since Variables: The time value plays important roles in the later analysis. We built the current date minus date of most recent transactions with the same card, merchant, card at this merchant, card in this zip code, card in this state.

Velocity change Variables: For these variables, the numerator is the number of transactions with the same card merchant over the past 0 or 1 day. The denominator is the average daily number of transactions with the same card merchant over the past 7, 14, 30 days.

The total number of variables is 410.

The list of all variables and their basic statistical features is attached in the appendix.

6. Feature Selection Process

After the variables are built, for the sake of avoiding the curse of dimensionality and eliminating the multicollinearity among variables, a filter and a wrapper will be used to do the feature selection. The filter is designed to filter out variables that cannot separate the labels properly based on the fraud detection rate (FDR) and univariate KS. For the retained variables, they would be passed to the RFECV (recursive feature elimination with cross-validation) function with a logistic regression model as a wrapper, and a certain combination of a bunch of variables that result in the best model performance would be selected as our final model input.

More specifically, to start with, FDR - a main and robust measure for fraud detection - of each variable is calculated. With a cutoff of 3%, it indicates what percentage of fraud would be caught in 3% of the population. In this step, the fraud label and a series of random numbers are appended to the dataset, in order to validate the reliability of the results, for they are supposed to rank the first and the last respectively. Then, all variables are ranked by their FDR, from low to high. Since KS measures how well the good and bad transactions can be separated, the KS of each variable is computed as well and then all variables are ranked again by these results. Finally, the average of the two rankings is used as the final ranking, and only the first 80 variables are retained.

After that, two-fold RFECV with logistic regression as the model and AUC of roc as the metric is used twice to do the further selection. First off, we z-scaled the input data to normalize the range of all features so that the model can speed up the learning and lead to faster convergence. RFEVC generates feature ranking with recursive feature elimination and cross-validated selection of the best number of features. Based on the results of the first round, variables ranked 51 to 80 are eliminated. Similarly, after running it for another time, only the top 30 variables are left as final model input.

Below is the list of retained variables.

#	variables	ks	FDR	rank_ks	rank_FDR	average_rank
0	Fraud	1	1	1	1	1
1	card_state_total_3	0.67411	0.630184	5	5.5	5.25
2	card_zip_total_3	0.674098	0.630184	6	5.5	5.75
3	card_merch_total_30	0.658621	0.550691	14	17	15.5
4	card_merch_total_3	0.680994	0.642857	3	2	2.5
5	Merchnum_total_1	0.596633	0.419355	43	50	46.5
6	Merchnum_max_3	0.570035	0.440092	67	45	56
7	card_merch_max_3	0.650209	0.475806	18	32	25
8	card_merch_max_30	0.653047	0.474654	17	34	25.5
9	card_merch_max_14	0.658537	0.475806	15	32	23.5
10	card_merch_avg_30	0.597262	0.293779	40	97.5	68.75
11	card_merch_avg_14	0.591444	0.292627	44	100	72
12	card_zip_total_1	0.659151	0.601382	13	7.5	10.25
13	Cardnum_total_1	0.577029	0.544931	56	18	37
14	card_merch_max_1	0.626285	0.457373	27	38	32.5
15	Cardnum_avg_0	0.570021	0.328341	68	66.5	67.25

16	Cardnum_max_0	0.585192	0.425115	51	48	49.5
17	Merchnum_max_7	0.534948	0.373272	101	60	80.5
18	card_state_total_14	0.668325	0.521889	9.5	20.5	15
19	Cardnum_total_14	0.547572	0.475806	95	32	63.5
20	Cardnum_max_14	0.525391	0.498848	103	23	63
21	Cardnum_total_0	0.57088	0.551843	65	16	40.5
22	card_merch_max_7	0.656559	0.465438	16	37	26.5
23	card_merch_avg_7	0.588654	0.293779	48	97.5	72.75
24	card_zip_avg_0	0.572621	0.323733	60.5	71.5	66
25	card_state_max_0	0.602495	0.419355	35.5	50	42.75
26	Merchnum_max_0	0.602326	0.4447	37	42	39.5
27	card_merch_total_7	0.686082	0.638249	2	3	2.5
28	Cardnum_total_7	0.600245	0.518433	39	22	30.5
29	Cardnum_med_1	0.557158	0.331797	87	64	75.5
30	Cardnum_avg_1	0.571881	0.354839	64	62	63

7. Algorithms

In this section, all algorithms used will be briefly described, including logistic regression as a baseline model, as well as a neural network, boosted trees, random forest, and SVM. With data of the last two months being retained as OOT set, the rest data is split into training and test sets by 8:2.

7.1 Baseline model

For this classification problem, a logistic regression model is used as the baseline model. A table of high-level results for logistic regression models is shown below.

Baseline	Parameter		Average FDR at 3%		
Logitstic Regression	# of Variables	Other Parameter	Train	Test	OOT
1	30	None	0.7090	0.6440	0.3020

7.2 Other regression models

We also tried Random Forest, Xgboost, Neural Network, and SVM models to solve the problem. After grid search the best parameters of each model, and calculate the FDR rate separately on the train, test, and OOT dataset. We include all the results information in the table below.

Model	Parameter							Average FDR at 3%		
Logistic Regression	# of Variables	CV	Class Weights	Cs	Regularization			Train	Test	OOT
1	30	10	(1,91)	0.001	L2			0.4020	0.3930	0.4000
2	30	10	(1,91)	0.1	L2			0.3970	0.3980	0.3970
3	30	10	(1,91)	10	L1(sage)			0.3630	0.3160	0.3530
4	30	10	(1,91)	10	L2			0.4000	0.3930	0.3990
5	30	10	(1,91)	100	L2			0.4320	0.4180	0.4290
Random Forest	# of Variables	# of Trees	# of Features	Class Weights	Sample Leaf	Sample Split	Depths	Train	Test	OOT
1	30	50	8	None	2	3	30	1.0000	0.8670	0.559
2	30	100	8	None	2	3	35	1.0000	0.8720	0.563
3	30	150	8	None	2	3	40	1.0000	0.8720	0.563
4	30	50	12	None	2	2	30	1.0000	0.8780	0.568
5	30	100	12	None	2	2	35	1.0000	0.8780	0.568
6	30	150	16	None	2	2	40	1.0000	0.8930	0.582
7	30	50	16	None	1	2	30	1.0000	0.8930	0.582
8	30	100	21	None	1	2	40	1.0000	0.8880	0.574
9	30	150	21	None	1	2	30	1.0000	0.8930	0.586
10	30	50	21	(1,91)	2	1	40	1.0000	0.8720	0.566
11	30	100	21	(1,91)	2	1	30	1.0000	0.8670	0.559
12	30	150	21	(1,91)	2	1	40	1.0000	0.8720	0.563
Xgboost	# of Features	# of Tree	# of Learning Rate	Depth				Train	Test	OOT
1	30	500	0.1	6				0.9013	0.8769	0.4754
2	30	500	0.1	10				0.9087	0.8864	0.3634
3	30	500	0.2	6				0.8942	0.8734	0.5527
4	30	1000	0.2	10				0.8991	0.8821	0.4942
5	30	1000	0.3	6				0.8743	0.8692	0.4525
6	30	1000	0.3	10				0.8806	0.8841	0.4642
7	25	1000	0.3	6				0.837	0.8451	0.5256
8	25	1000	0.3	10				0.8567	0.8245	0.4472
9	20	500	0.2	10				0.8429	0.8356	0.4375
10	20	1000	0.1	10				0.8398	0.8276	0.4390
Neural Network	# of layers	# of nodes	# of epochs	Class Weights	Notes			Train	Test	OOT
1	1	30	100	(0.5, 8)	adam, BCE			0.7376	0.5659	0.4693
2	1	30	100	(1,91)	adam, BCE			0.7376	0.5824	0.4804
3	1	8	100	(1,91)	SGD, BCE			0.6443	0.6538	0.2123
4	2	(8,4)	100	(1,91)	adam, BCE			0.6997	0.6098	0.4357
5	2	(12,8)	100	(1,91)	adam, BCE			0.7274	0.5824	0.5083
6	3	(12,8,4)	100	(1,91)	adam, BCE			0.7244	0.5989	0.4916
7	2	(12,8)	100	(1,91)	adam, BCE, learning_rate=0.01			0.6356	0.5549	0.4358
8	2	(12,8)	100	(1,91)	adam, BCE, dropout			0.7071	0.5714	0.4301
SVM	Kernel	C			Gamma			Train	Test	OOT
1	RBF	1000			0.01			0.8632	0.7340	0.3575
2	RBF	1000			0.001			0.7353	0.6277	0.4637
3	RBF	1000			0.0001			0.6529	0.5691	0.4190
4	RBF	2000			0.01			0.8809	0.7340	0.3240
5	RBF	2000			0.001			0.7515	0.6436	0.4693
6	RBF	3000			0.001			0.7559	0.6596	0.4637

8. Results:

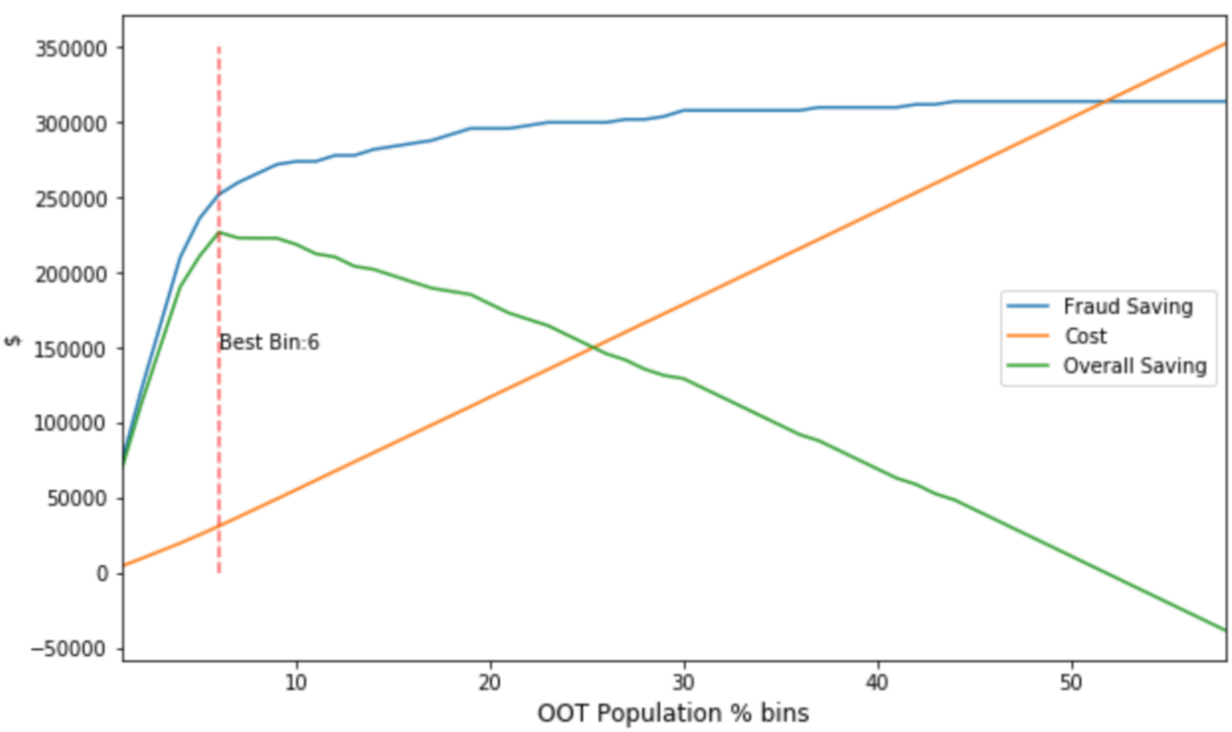
Having compared models’ FDRs, we chose random forest as our final model, and below are three tables for three datasets.

Training	# Records		# Goods		# Bads		Fraud Rate					
	72568		71788		780		1.07%					
	Bin Statistics						Cumulative Statistics					
Population Bin %	# Records	# Goods	# Bads	% Goods	% Bads	Total # Records	Cumulative Good	Cumulative Bad	Cumulative % Goods	Cumulative % Bads(FDR)	KS	FPR
1	726	8	718	1	99	726	8	718	0.01	92.05	92.04	0.01
2	726	664	62	91	9	1452	672	780	0.94	100.00	99.06	0.86
3	726	726	0	100	0	2178	1398	780	1.95	100.00	98.05	1.79
4	725	725	0	100	0	2903	2123	780	2.96	100.00	97.04	2.72
5	726	726	0	100	0	3629	2849	780	3.97	100.00	96.03	3.65
6	726	726	0	100	0	4355	3575	780	4.98	100.00	95.02	4.58
7	725	725	0	100	0	5080	4300	780	5.99	100.00	94.01	5.51
8	726	726	0	100	0	5806	5026	780	7.00	100.00	93.00	6.44
9	726	726	0	100	0	6532	5752	780	8.01	100.00	91.99	7.37
10	725	725	0	100	0	7257	6477	780	9.02	100.00	90.98	8.30
11	726	726	0	100	0	7983	7203	780	10.03	100.00	89.97	9.23
12	726	726	0	100	0	8709	7929	780	11.05	100.00	88.95	10.17
13	725	725	0	100	0	9434	8654	780	12.05	100.00	87.95	11.09
14	726	726	0	100	0	10160	9380	780	13.07	100.00	86.93	12.03
15	726	726	0	100	0	10886	10106	780	14.08	100.00	85.92	12.96
16	725	725	0	100	0	11611	10831	780	15.09	100.00	84.91	13.89
17	726	726	0	100	0	12337	11557	780	16.10	100.00	83.90	14.82
18	726	726	0	100	0	13063	12283	780	17.11	100.00	82.89	15.75
19	725	725	0	100	0	13788	13008	780	18.12	100.00	81.88	16.68
20	726	726	0	100	0	14514	13734	780	19.13	100.00	80.87	17.61

Test	# Records		# Goods		# Bads		Fraud Rate					
	8064		7976		88		1.09%					
	Bin Statistics						Cumulative Statistics					
Population Bin %	# Records	# Goods	# Bads	% Goods	% Bads	Total # Records	Cumulative Good	Cumulative Bad	Cumulative % Goods	Cumulative % Bads(FDR)	KS	FPR
1	81	15	66	19	81	81	15	66	0.19	75.00	74.81	0.23
2	81	71	10	88	12	162	86	76	1.08	86.36	85.29	1.13
3	80	78	2	98	3	242	164	78	2.06	88.64	86.58	2.10
4	81	78	3	96	4	323	242	81	3.03	92.05	89.01	2.99
5	81	80	1	99	1	404	322	82	4.04	93.18	89.14	3.93
6	80	80	0	100	0	484	402	82	5.04	93.18	88.14	4.90
7	81	79	2	98	2	565	481	84	6.03	95.45	89.42	5.73
8	81	81	0	100	0	646	562	84	7.05	95.45	88.41	6.69
9	80	80	0	100	0	726	642	84	8.05	95.45	87.41	7.64
10	81	81	0	100	0	807	723	84	9.06	95.45	86.39	8.61
11	80	80	0	100	0	887	803	84	10.07	95.45	85.39	9.56
12	81	80	1	99	1	968	883	85	11.07	96.59	85.52	10.39
13	81	80	1	99	1	1049	963	86	12.07	97.73	85.65	11.20
14	80	80	0	100	0	1129	1043	86	13.08	97.73	84.65	12.13
15	81	81	0	100	0	1210	1124	86	14.09	97.73	83.63	13.07
16	81	81	0	100	0	1291	1205	86	15.11	97.73	82.62	14.01
17	80	80	0	100	0	1371	1285	86	16.11	97.73	81.62	14.94
18	81	81	0	100	0	1452	1366	86	17.13	97.73	80.60	15.88
19	80	80	0	100	0	1532	1446	86	18.13	97.73	79.60	16.81
20	81	81	0	100	0	1613	1527	86	19.14	97.73	78.58	17.76

Out of Time	# Records		# Goods		# Bads		Fraud Rate					
	12427		12248		179		1.44%					
	Bin Statistics						Cumulative Statistics					
Population Bin %	# Records	# Goods	# Bads	% Goods	% Bads	Total # Records	Cumulative Good	Cumulative Bad	Cumulative % Goods	Cumulative % Bads(FDR)	KS	FPR
1	125	88	37	70	30	125	88	37	0.72	20.67	19.95	2.38
2	124	100	24	81	19	249	188	61	1.53	34.08	32.54	3.08
3	124	102	22	82	18	373	290	83	2.37	46.37	44.00	3.49
4	125	103	22	82	18	498	393	105	3.21	58.66	55.45	3.74
5	124	111	13	90	10	622	504	118	4.11	65.92	61.81	4.27
6	124	116	8	94	6	746	620	126	5.06	70.39	65.33	4.92
7	124	120	4	97	3	870	740	130	6.04	72.63	66.58	5.69
8	125	122	3	98	2	995	862	133	7.04	74.30	67.26	6.48
9	124	121	3	98	2	1119	983	136	8.03	75.98	67.95	7.23
10	124	123	1	99	1	1243	1106	137	9.03	76.54	67.51	8.07
11	124	124	0	100	0	1367	1230	137	10.04	76.54	66.49	8.98
12	125	123	2	98	2	1492	1353	139	11.05	77.65	66.61	9.73
13	124	124	0	100	0	1616	1477	139	12.06	77.65	65.59	10.63
14	124	122	2	98	2	1740	1599	141	13.06	78.77	65.72	11.34
15	124	123	1	99	1	1864	1722	142	14.06	79.33	65.27	12.13
16	125	124	1	99	1	1989	1846	143	15.07	79.89	64.82	12.91
17	124	123	1	99	1	2113	1969	144	16.08	80.45	64.37	13.67
18	124	122	2	98	2	2237	2091	146	17.07	81.56	64.49	14.32
19	124	122	2	98	2	2361	2213	148	18.07	82.68	64.61	14.95
20	125	125	0	100	0	2486	2338	148	19.09	82.68	63.59	15.80

Assuming the credit card issuing bank gains $2000 for every correctly identified fraud transaction while loses $50 for every falsely labelled normal transaction, our algorithm-based system can save $226800 by checking 6% transaction of OOT data.



9. Conclusions:

In this credit card transaction fraud detection project, we started with looking into the data on hand, removed the irrelevant observations and unreliable outliers, and filled in the missing values under critical fields in line with rules of thumb. We then create 299 features to capture the frequency, amount, change in days, and velocity of transaction within various groups. To avoid the curse of dimensionality, we downsized the number of features from 299 to 30. Building multiple state-of-the-art models using the selected features, we see how models perform in regards to the Fraud Detection Rate at 3%. As the FDR of a random forest model stands out, we named it as our final model. We finally evaluated the profitability of this algorithm-based system on OOT data and it shows that our system successfully saves $226,800 by checking 6% of 12427 OOT transactions.

In the future, we may further optimize the performance of our model by leveraging a more complicated grid search process and by training on more transaction data. We could create an ensemble model to synthesize all model predictions together with different weights. Since models generally learn better from balanced datasets, we could also adjust the ratio of fraudulent and normal transactions in our training data by downsampling the normal record or upsampling the fraudulent records. SMOTE algorithm can be used to artificially invent new frauds to modify the ratio of the goods and bads.

10. Appendix:

The list of all variables and their basic statistical features

Variable Name	min	max	mean	std
Cardnum_day_since	0	356	5.41985746	17.187933
Cardnum_count_0	1	146	2.47365582	6.0021162
Cardnum_avg_0	0.01	28392.84	393.55749	726.845846
Cardnum_max_0	0.01	47900	498.205809	1030.95736
Cardnum_med_0	0.01	28392.84	381.352185	718.729093
Cardnum_total_0	0.01	218301.83	741.645565	3431.44613
Cardnum_actual/avg_0	4.20E-05	23.791234	1.00195358	0.44492847
Cardnum_actual/max_0	1.42E-05	1	0.87522979	0.28284808
Cardnum_actual/med_0	8.95E-05	657.894737	1.4103175	9.89588972
Cardnum_actual/toal_0	1.40E-05	1	0.77275828	0.35027538
Cardnum_count_1	1	177	3.36710686	7.94499458
Cardnum_avg_1	0.01	28392.84	395.450686	675.825659
Cardnum_max_1	0.01	47900	610.873046	1212.86427
Cardnum_med_1	0.01	28392.84	364.221874	658.721561
Cardnum_total_1	0.01	307468.06	1110.04559	5669.43413
Cardnum_actual/avg_1	5.53E-05	23.791234	0.99817071	0.64016607
Cardnum_actual/max_1	1.42E-05	1	0.77217493	0.35850507
Cardnum_actual/med_1	8.95E-05	674.761134	1.83299461	13.3512071
Cardnum_actual/toal_1	1.38E-05	1	0.63596936	0.39374583
Cardnum_count_3	1	251	4.79426746	11.450064
Cardnum_avg_3	0.01	28392.84	395.85293	629.374341
Cardnum_max_3	0.01	47900	739.785998	1367.57849
Cardnum_med_3	0.01	28392.84	341.356881	592.648531
Cardnum_total_3	0.01	310843.06	1512.93295	6115.50533
Cardnum_actual/avg_3	5.53E-05	38.0025967	1.00241463	0.84290181
Cardnum_actual/max_3	1.42E-05	1	0.67357018	0.39736955
Cardnum_actual/med_3	0.00022614	1570.85562	2.34058801	17.1229589
Cardnum_actual/toal_3	1.38E-05	1	0.51377011	0.40048741
Cardnum_count_7	1	369	7.62779962	16.6126417
Cardnum_avg_7	0.14	25500	397.185701	560.07571
Cardnum_max_7	0.14	47900	960.428911	1603.12914
Cardnum_med_7	0.14	25500	307.158748	501.730772
Cardnum_total_7	0.14	312616.06	2384.0361	7158.50084

Cardnum_actual/avg_7	5.53E-05	59.8675047	0.99446325	1.07728473
Cardnum_actual/max_7	1.42E-05	1	0.53717639	0.41278372
Cardnum_actual/med_7	0.00016393	5747.53846	2.98565647	27.0911559
Cardnum_actual/toal_7	1.38E-05	1	0.35753001	0.36726486
Cardnum_count_14	1	380	11.8000145	20.7179332
Cardnum_avg_14	0.14	25500	396.993474	522.916559
Cardnum_max_14	0.14	47900	1188.63697	1829.49957
Cardnum_med_14	0.14	25500	279.015598	456.124708
Cardnum_total_14	0.14	313995.06	3768.18381	9421.91738
Cardnum_actual/avg_14	5.53E-05	71.3321667	0.99836381	1.27307191
Cardnum_actual/max_14	1.42E-05	1	0.4373109	0.40016372
Cardnum_actual/med_14	0.00013931	6145.63636	3.47249671	29.2461151
Cardnum_actual/toal_14	1.31E-05	1	0.25099281	0.31730532
Cardnum_count_30	1	426	20.3594614	30.9067105
Cardnum_avg_30	0.17	25500	396.584504	479.342519
Cardnum_max_30	0.17	47900	1482.17473	2076.87614
Cardnum_med_30	0.17	25500	250.941946	402.426408
Cardnum_total_30	0.17	353997.29	6675.65442	14591.2329
Cardnum_actual/avg_30	5.01E-05	137.986966	1.00552153	1.61079231
Cardnum_actual/max_30	9.37E-06	1	0.34343149	0.36903176
Cardnum_actual/med_30	0.00011996	6288.55814	3.95241186	32.6133115
Cardnum_actual/toal_30	5.13E-06	1	0.15875375	0.25126121
Merchnum_day_since	0	364	31.6865981	68.2577483
Merchnum_count_0	1	260	6.79373839	18.9938861
Merchnum_avg_0	0.01	47900	395.794591	775.938085
Merchnum_max_0	0.01	47900	500.326857	998.219348
Merchnum_med_0	0.01	47900	382.260959	767.496183
Merchnum_total_0	0.01	217467.18	774.611046	2839.96172
Merchnum_actual/avg_0	8.95E-05	37.9561425	1.00288631	0.6270007
Merchnum_actual/max_0	4.47E-05	1	0.8149021	0.33893634
Merchnum_actual/med_0	8.95E-05	405.449591	1.24187981	3.08962593
Merchnum_actual/toal_0	4.47E-05	1	0.72253503	0.393326
Merchnum_count_1	1	327	11.5460958	31.6312534
Merchnum_avg_1	0.01	47900	397.518079	764.493198
Merchnum_max_1	0.01	47900	580.480637	1132.75819
Merchnum_med_1	0.01	47900	372.754091	754.700235
Merchnum_total_1	0.01	306633.41	1114.73315	4361.00156
Merchnum_actual/avg_1	8.95E-05	43.4260216	0.9997102	0.76357025
Merchnum_actual/max_1	4.47E-05	1	0.74725015	0.38034584

Merchnum_actual/med_1	8.95E-05	405.449591	1.3574298	3.93897463
Merchnum_actual/toal_1	4.47E-05	1	0.63952223	0.41948553
Merchnum_count_3	1	466	20.9715448	55.2021196
Merchnum_avg_3	0.01	47900	397.579383	744.575217
Merchnum_max_3	0.01	47900	664.769125	1213.01888
Merchnum_med_3	0.01	47900	363.231408	733.761882
Merchnum_total_3	0.01	307302.58	1565.27124	5158.7647
Merchnum_actual/avg_3	8.95E-05	64.0928065	0.99975026	0.91642124
Merchnum_actual/max_3	4.47E-05	1	0.69182338	0.40495872
Merchnum_actual/med_3	8.95E-05	467.828571	1.43802739	4.26800534
Merchnum_actual/toal_3	1.80E-05	1	0.57506045	0.43213731
Merchnum_count_7	1	762	42.0651888	106.196602
Merchnum_avg_7	0.01	47900	396.590591	708.830348
Merchnum_max_7	0.01	47900	811.316159	1345.59013
Merchnum_med_7	0.01	47900	348.099903	698.196298
Merchnum_total_7	0.01	313984.55	2582.76684	6312.01956
Merchnum_actual/avg_7	0.00012442	82.4605985	0.9969724	1.09120294
Merchnum_actual/max_7	4.47E-05	1	0.61933075	0.42367933
Merchnum_actual/med_7	0.00013503	473.984211	1.54082696	4.52518599
Merchnum_actual/toal_7	1.76E-05	1	0.48585261	0.43405234
Merchnum_count_14	1	1091	75.8969159	192.022469
Merchnum_avg_14	0.01	47900	398.016245	679.786219
Merchnum_max_14	0.01	47900	972.090878	1536.88781
Merchnum_med_14	0.01	47900	337.607076	662.267915
Merchnum_total_14	0.01	319334.68	4258.04795	8747.21679
Merchnum_actual/avg_14	0.00012386	133.533335	0.99537666	1.26160609
Merchnum_actual/max_14	4.47E-05	1	0.56318857	0.42917932
Merchnum_actual/med_14	0.00013503	518.070249	1.60860668	4.86413729
Merchnum_actual/toal_14	1.63E-05	1	0.41819303	0.42585243
Merchnum_count_30	1	1828	146.322106	376.587731
Merchnum_avg_30	0.01	47900	397.079814	637.247347
Merchnum_max_30	0.01	47900	1205.78571	1840.22469
Merchnum_med_30	0.01	47900	323.540508	607.348076
Merchnum_total_30	0.01	320373	7785.54768	13940.632
Merchnum_actual/avg_30	5.05E-05	172.635884	0.99685664	1.44303707
Merchnum_actual/max_30	1.83E-05	1	0.50339186	0.42742223
Merchnum_actual/med_30	6.75E-05	481.588235	1.67017687	4.64798922
Merchnum_actual/toal_30	6.13E-06	1	0.34840349	0.40856706
Merch_zip_day_since	0	364	12.0397627	36.775633

Merch_zip_count_0	1	261	7.30321483	19.4486534
Merch_zip_avg_0	0.01	28392.84	394.903694	737.569892
Merch_zip_max_0	0.01	47900	552.857065	1048.76171
Merch_zip_med_0	0.01	28392.84	373.065985	726.582521
Merch_zip_total_0	0.01	217467.18	899.741188	2940.61364
Merch_zip_actual/avg_0	8.95E-05	39.6996321	1.00148984	0.76155747
Merch_zip_actual/max_0	4.47E-05	1	0.76975049	0.36816559
Merch_zip_actual/med_0	8.95E-05	598.380567	1.42923844	5.88847942
Merch_zip_actual/toal_0	4.47E-05	1	0.66781426	0.40910777
Merch_zip_count_1	1	337	12.9697916	33.0509329
Merch_zip_avg_1	0.01	28392.84	398.078066	719.075508
Merch_zip_max_1	0.01	47900	695.981854	1251.56661
Merch_zip_med_1	0.01	28392.84	356.403049	697.554034
Merch_zip_total_1	0.01	306633.41	1448.25394	4593.60829
Merch_zip_actual/avg_1	0.00011848	83.1415448	1.00118416	1.15604594
Merch_zip_actual/max_1	4.47E-05	1	0.67162057	0.41038134
Merch_zip_actual/med_1	0.00033704	604.087194	1.66481563	7.36546396
Merch_zip_actual/toal_1	9.68E-06	1	0.54976981	0.42755889
Merch_zip_count_3	1	481	23.8477442	57.753722
Merch_zip_avg_3	0.01	28392.84	397.860388	674.757825
Merch_zip_max_3	0.01	47900	856.281664	1391.25959
Merch_zip_med_3	0.01	28392.84	339.143379	643.796439
Merch_zip_total_3	0.01	307302.58	2258.38309	5785.57253
Merch_zip_actual/avg_3	0.00014129	105.063088	0.99882417	1.39250208
Merch_zip_actual/max_3	4.47E-05	1	0.59532643	0.42814664
Merch_zip_actual/med_3	0.00015476	680.653951	1.8270465	8.22257333
Merch_zip_actual/toal_3	5.17E-06	1	0.46436779	0.42611358
Merch_zip_count_7	1	784	48.4262685	111.748242
Merch_zip_avg_7	0.01	27218	396.285504	618.709845
Merch_zip_max_7	0.01	47900	1102.4092	1612.27857
Merch_zip_med_7	0.01	27218	316.542365	586.953788
Merch_zip_total_7	0.01	313984.55	4074.71126	7829.00316
Merch_zip_actual/avg_7	0.00013503	138.143954	0.99463472	1.56834475
Merch_zip_actual/max_7	4.47E-05	1	0.50245265	0.42811703
Merch_zip_actual/med_7	0.00013503	680.653951	1.97978899	8.44112942
Merch_zip_actual/toal_7	4.84E-06	1	0.35495216	0.40129961
Merch_zip_count_14	1	1119	88.4741123	202.907108
Merch_zip_avg_14	0.01	26910	396.947856	576.197037
Merch_zip_max_14	0.01	47900	1368.4636	1899.57194

Merch_zip_med_14	0.01	26910	298.948156	538.571456
Merch_zip_total_14	0.01	319334.68	7072.48524	11897.1327
Merch_zip_actual/avg_14	0.00012672	191.218538	0.99405328	1.75457912
Merch_zip_actual/max_14	2.88E-05	1	0.43186953	0.41632719
Merch_zip_actual/med_14	0.00013503	680.653951	2.0742229	8.30728039
Merch_zip_actual/toal_14	4.15E-06	1	0.27745922	0.3691935
Merch_zip_count_30	1	1878	174.544872	401.743034
Merch_zip_avg_30	0.17	26910	395.88242	523.106201
Merch_zip_max_30	0.17	47900	1758.09222	2372.20303
Merch_zip_med_30	0.17	26910	279.676761	483.108107
Merch_zip_total_30	0.17	320373	13711.7375	21564.1038
Merch_zip_actual/avg_30	1.78E-05	241.127469	0.99526725	1.91645133
Merch_zip_actual/max_30	5.48E-06	1	0.3608961	0.39385927
Merch_zip_actual/med_30	2.50E-05	5082.25	2.22695693	18.138764
Merch_zip_actual/toal_30	2.06E-06	1	0.20522087	0.32706604
card_merch_day_since	0	364	82.5557953	100.335913
card_merch_count_0	1	145	2.08493003	5.90330194
card_merch_avg_0	0.01	47900	396.036532	807.484917
card_merch_max_0	0.01	47900	421.052846	935.627696
card_merch_med_0	0.01	47900	393.715475	801.255183
card_merch_total_0	0.01	217467.18	526.193556	2619.17479
card_merch_actual/avg_0	8.95E-05	20.2424767	0.99972723	0.21940351
card_merch_actual/max_0	4.47E-05	1	0.95718912	0.16534573
card_merch_actual/med_0	8.95E-05	100	1.02582677	0.66528734
card_merch_actual/toal_0	4.47E-05	1	0.88646035	0.27301431
card_merch_count_1	1	177	2.40431756	7.5884802
card_merch_avg_1	0.01	47900	397.502383	810.408295
card_merch_max_1	0.01	47900	432.277061	1010.09534
card_merch_med_1	0.01	47900	394.78607	804.993216
card_merch_total_1	0.01	306633.41	596.63259	4018.44087
card_merch_actual/avg_1	8.95E-05	20.2424767	0.9971393	0.25336752
card_merch_actual/max_1	4.47E-05	1	0.94187185	0.19254486
card_merch_actual/med_1	8.95E-05	71.1111111	1.03152574	0.69403194
card_merch_actual/toal_1	4.47E-05	1	0.86088357	0.2972382
card_merch_count_3	1	248	3.01325767	10.9733611
card_merch_avg_3	0.01	47900	398.437284	808.245646
card_merch_max_3	0.01	47900	441.065104	1014.38939
card_merch_med_3	0.01	47900	395.034384	803.137377
card_merch_total_3	0.01	306633.41	628.037781	4061.03013

card_merch_actual/avg_3	8.95E-05	20.2424767	0.99462753	0.29494184
card_merch_actual/max_3	4.47E-05	1	0.92165387	0.22212287
card_merch_actual/med_3	8.95E-05	301.103152	1.05231676	1.49387589
card_merch_actual/toal_3	4.47E-05	1	0.83020306	0.32331105
card_merch_count_7	1	358	4.03601772	15.6532377
card_merch_avg_7	0.01	47900	400.165734	803.837699
card_merch_max_7	0.01	47900	458.472361	1022.57377
card_merch_med_7	0.01	47900	395.06859	799.188193
card_merch_total_7	0.01	306633.41	686.825437	4101.90274
card_merch_actual/avg_7	8.95E-05	20.2424767	0.98920764	0.36113191
card_merch_actual/max_7	4.47E-05	1	0.88836411	0.26222309
card_merch_actual/med_7	8.95E-05	442.869796	1.07864474	2.19380361
card_merch_actual/toal_7	4.47E-05	1	0.78260837	0.35546435
card_merch_count_14	1	369	5.32503086	19.0446263
card_merch_avg_14	0.01	47900	402.14139	801.058192
card_merch_max_14	0.01	47900	479.538874	1043.23252
card_merch_med_14	0.01	47900	395.106227	797.263582
card_merch_total_14	0.01	306633.41	766.516491	4166.11386
card_merch_actual/avg_14	8.95E-05	23.1132169	0.9868074	0.42977037
card_merch_actual/max_14	4.47E-05	1	0.85548049	0.29332501
card_merch_actual/med_14	8.95E-05	400	1.10910595	2.25628573
card_merch_actual/toal_14	4.47E-05	1	0.73718536	0.37857601
card_merch_count_30	1	409	7.7154372	27.4324023
card_merch_avg_30	0.01	47900	404.192356	795.519915
card_merch_max_30	0.01	47900	511.457917	1065.14993
card_merch_med_30	0.01	47900	393.747171	794.760519
card_merch_total_30	0.01	306633.41	918.45131	4296.50513
card_merch_actual/avg_30	0.00010127	25.0256401	0.98326714	0.51166481
card_merch_actual/max_30	4.47E-05	1	0.81152218	0.3269365
card_merch_actual/med_30	6.75E-05	397.860963	1.14665592	2.23394619
card_merch_actual/toal_30	3.09E-05	1	0.67834382	0.3997069
card_zip_day_since	0	364	70.7165161	93.1861326
card_zip_count_0	1	146	2.11484797	5.93676611
card_zip_avg_0	0.01	28392.84	395.559105	794.348972
card_zip_max_0	0.01	47900	422.80831	936.637617
card_zip_med_0	0.01	28392.84	393.009157	788.040791
card_zip_total_0	0.01	217467.18	531.60934	2623.02185
card_zip_actual/avg_0	8.95E-05	20.2424767	0.99995754	0.23237016
card_zip_actual/max_0	4.47E-05	1	0.95245906	0.17488884

card_zip_actual/med_0	8.95E-05	234.792818	1.03421659	1.09509009
card_zip_actual/toal_0	4.47E-05	1	0.87907744	0.27952764
card_zip_count_1	1	177	2.47316825	7.81844715
card_zip_avg_1	0.01	28392.84	397.124113	796.773026
card_zip_max_1	0.01	47900	435.509968	1012.08719
card_zip_med_1	0.01	28392.84	394.069503	791.28732
card_zip_total_1	0.01	306633.41	605.585303	4022.61362
card_zip_actual/avg_1	8.95E-05	20.1712925	0.99700103	0.27855574
card_zip_actual/max_1	4.47E-05	1	0.93358496	0.20644258
card_zip_actual/med_1	8.95E-05	231.594005	1.04383394	1.15444346
card_zip_actual/toal_1	4.47E-05	1	0.8492262	0.30614152
card_zip_count_3	1	251	3.12521137	11.2814695
card_zip_avg_3	0.01	28392.84	398.070003	793.856062
card_zip_max_3	0.01	47900	446.528102	1018.30474
card_zip_med_3	0.01	28392.84	393.95087	788.564479
card_zip_total_3	0.01	306633.41	641.938507	4066.81703
card_zip_actual/avg_3	8.95E-05	20.1712925	0.99406678	0.326126
card_zip_actual/max_3	4.47E-05	1	0.90913817	0.23975367
card_zip_actual/med_3	8.95E-05	301.103152	1.07352001	1.95750871
card_zip_actual/toal_3	4.47E-05	1	0.8143799	0.33354918
card_zip_count_7	1	369	4.24747658	16.3066713
card_zip_avg_7	0.01	28392.84	399.913177	787.669625
card_zip_max_7	0.01	47900	467.750092	1029.1879
card_zip_med_7	0.01	28392.84	393.622981	782.960855
card_zip_total_7	0.01	306633.41	710.58082	4112.38817
card_zip_actual/avg_7	8.95E-05	32.7630071	0.98785491	0.40771683
card_zip_actual/max_7	4.47E-05	1	0.86910935	0.28315023
card_zip_actual/med_7	8.95E-05	442.869796	1.11817892	3.11392719
card_zip_actual/toal_7	4.47E-05	1	0.76020432	0.36624084
card_zip_count_14	1	380	5.69505275	19.9782092
card_zip_avg_14	0.01	28392.84	402.216869	785.376883
card_zip_max_14	0.01	47900	494.39391	1055.66474
card_zip_med_14	0.01	28392.84	393.051098	780.428547
card_zip_total_14	0.01	306633.41	806.14342	4187.0149
card_zip_actual/avg_14	8.95E-05	32.7630071	0.98485327	0.48477613
card_zip_actual/max_14	4.47E-05	1	0.82975614	0.31609988
card_zip_actual/med_14	8.95E-05	449.684969	1.1610107	3.36476891
card_zip_actual/toal_14	4.47E-05	1	0.70761712	0.38895633
card_zip_count_30	1	425	8.41571833	28.9504203

card_zip_avg_30	0.01	28392.84	404.300197	776.446745
card_zip_max_30	0.01	47900	535.260346	1087.19532
card_zip_med_30	0.01	28392.84	390.236174	774.548638
card_zip_total_30	0.01	306633.41	989.783327	4345.226
card_zip_actual/avg_30	0.00010127	33.8255898	0.98139273	0.58362704
card_zip_actual/max_30	4.47E-05	1	0.77803675	0.34933435
card_zip_actual/med_30	6.75E-05	2248.7	1.24701592	8.20046722
card_zip_actual/toal_30	3.09E-05	1	0.63914479	0.4080648
card_state_day_since	0	364	37.8289366	66.8639734
card_state_count_0	1	146	2.16336608	5.93645489
card_state_avg_0	0.01	28392.84	395.224702	786.732847
card_state_max_0	0.01	47900	432.408216	944.344605
card_state_med_0	0.01	28392.84	391.823445	780.414881
card_state_total_0	0.01	217467.18	553.892402	2640.44341
card_state_actual/avg_0	8.95E-05	20.2424767	1.00074751	0.26265423
card_state_actual/max_0	4.47E-05	1	0.94103059	0.19530366
card_state_actual/med_0	8.95E-05	390.743707	1.05394898	1.99681013
card_state_actual/toal_0	4.47E-05	1	0.86136017	0.2937661
card_state_count_1	1	177	2.5873523	7.8161433
card_state_avg_1	0.01	28392.84	396.856617	784.28833
card_state_max_1	0.01	47900	457.921623	1030.27358
card_state_med_1	0.01	28392.84	391.14018	778.578966
card_state_total_1	0.01	306633.41	659.237492	4054.2892
card_state_actual/avg_1	8.95E-05	20.1712925	0.99782365	0.33311256
card_state_actual/max_1	4.47E-05	1	0.90850761	0.24105165
card_state_actual/med_1	8.95E-05	390.743707	1.08249248	2.14983655
card_state_actual/toal_1	4.47E-05	1	0.81152668	0.32997441
card_state_count_3	1	251	3.33518678	11.2737868
card_state_avg_3	0.01	28392.84	397.763745	771.833833
card_state_max_3	0.01	47900	487.096649	1059.92832
card_state_med_3	0.01	28392.84	387.864903	765.070956
card_state_total_3	0.01	306633.41	739.961853	4122.89944
card_state_actual/avg_3	8.95E-05	20.1712925	0.99453416	0.40561268
card_state_actual/max_3	4.47E-05	1	0.86787704	0.28445493
card_state_actual/med_3	8.95E-05	390.743707	1.13769782	2.78223354
card_state_actual/toal_3	4.47E-05	1	0.75468093	0.36250089
card_state_count_7	1	369	4.67184663	16.2896557
card_state_avg_7	0.01	28392.84	399.857813	755.30695
card_state_max_7	0.01	47900	542.623176	1126.33149

card_state_med_7	0.01	28392.84	381.105909	744.326024
card_state_total_7	0.01	306633.41	906.816075	4250.36592
card_state_actual/avg_7	8.95E-05	32.7630071	0.99035468	0.5233023
card_state_actual/max_7	4.47E-05	1	0.80302672	0.33432244
card_state_actual/med_7	8.95E-05	442.869796	1.24615596	4.20256436
card_state_actual/toal_7	4.47E-05	1	0.66734739	0.39428592
card_state_count_14	1	380	6.46270112	19.9547267
card_state_avg_14	0.01	28392.84	401.697616	734.257784
card_state_max_14	0.01	47900	608.554209	1195.13648
card_state_med_14	0.01	28392.84	372.72079	725.50668
card_state_total_14	0.01	306633.41	1158.20691	4513.97825
card_state_actual/avg_14	8.95E-05	23.2049107	0.98930307	0.62958071
card_state_actual/max_14	4.47E-05	1	0.73972499	0.3674077
card_state_actual/med_14	8.95E-05	456.564171	1.35641202	4.80616374
card_state_actual/toal_14	4.47E-05	1	0.58557031	0.40929289
card_state_count_30	1	425	9.90589956	28.914517
card_state_avg_30	0.01	28392.84	402.907232	692.797392
card_state_max_30	0.01	47900	715.868799	1316.21826
card_state_med_30	0.01	28392.84	357.558616	676.249407
card_state_total_30	0.01	306633.41	1682.20548	5199.28447
card_state_actual/avg_30	3.55E-05	33.8255898	0.98788127	0.76404486
card_state_actual/max_30	9.37E-06	1	0.65883134	0.39384301
card_state_actual/med_30	6.75E-05	607.785888	1.5063028	5.60172544
card_state_actual/toal_30	7.11E-06	1	0.48567845	0.41040123
Cardnum_avg_Cardnumcount17	3.52E-05	100	0.2638862	1.76596971
Cardnum_avg_Cardnumsum17	1	177	3.36710686	7.94499458
Cardnum_avg_Cardnumcount114	3.52E-05	100	0.2638862	1.76596971
Cardnum_avg_Cardnumsum114	1	177	3.36710686	7.94499458
Cardnum_avg_Cardnumcount130	3.52E-05	100	0.2638862	1.76596971
Cardnum_avg_Cardnumsum130	1	177	3.36710686	7.94499458
Cardnum_avg_Cardnumcount07	3.52E-05	100	0.19947057	1.26912596
Cardnum_avg_Cardnumsum07	0.00048565	135.075759	2.35420599	5.36407773
Cardnum_avg_Cardnumcount014	3.52E-05	100	0.19947057	1.26912596
Cardnum_avg_Cardnumsum014	0.00048565	135.075759	2.35420599	5.36407773
Cardnum_avg_Cardnumcount030	3.52E-05	100	0.19947057	1.26912596
Cardnum_avg_Cardnumsum030	0.00048565	135.075759	2.35420599	5.36407773
Merchnum_avg_Cardnumcount17	2.09E-05	100	1.30247074	4.81114431
Merchnum_avg_Cardnumsum17	1	327	11.5460958	31.6312534
Merchnum_avg_Cardnumcount114	2.09E-05	100	1.30247074	4.81114431

Merchnum_avg_Cardnumsum114	1	327	11.5460958	31.6312534
Merchnum_avg_Cardnumcount130	2.09E-05	100	1.30247074	4.81114431
Merchnum_avg_Cardnumsum130	1	327	11.5460958	31.6312534
Merchnum_avg_Cardnumcount07	2.09E-05	100	0.74982273	3.04829953
Merchnum_avg_Cardnumsum07	0.00048565	253.72911	6.56444813	18.290131
Merchnum_avg_Cardnumcount014	2.09E-05	100	0.74982273	3.04829953
Merchnum_avg_Cardnumsum014	0.00048565	253.72911	6.56444813	18.290131
Merchnum_avg_Cardnumcount030	2.09E-05	100	0.74982273	3.04829953
Merchnum_avg_Cardnumsum030	0.00048565	253.72911	6.56444813	18.290131
Merch_state_day_since	0	228	0.21738228	1.88359357
Merch_state_count_0	1	261	13.4948079	19.7004832
Merch_state_avg_0	0.22	28392.84	395.690075	503.330841
Merch_state_max_0	0.22	47900	1307.4384	1800.11682
Merch_state_med_0	0.22	28392.84	261.070773	447.413869
Merch_state_total_0	0.22	218301.35	3730.38895	5518.40064
Merch_state_actual/avg_0	1.72E-05	128.850853	1.00535483	1.4273019
Merch_state_actual/max_0	4.17E-06	1	0.42496615	0.40230776
Merch_state_actual/med_0	2.39E-05	3685.35912	2.47183395	18.7472989
Merch_state_actual/toal_0	5.53E-07	1	0.25902006	0.33988883
Merch_state_count_1	1	339	29.7760926	32.8294743
Merch_state_avg_1	0.36	28392.84	397.375635	389.432527
Merch_state_max_1	0.36	47900	2023.84558	2457.61736
Merch_state_med_1	0.36	28392.84	211.838877	295.225124
Merch_state_total_1	0.36	315347.01	9105.32357	10357.8062
Merch_state_actual/avg_1	1.77E-05	196.577065	1.01056705	1.97379507
Merch_state_actual/max_1	3.90E-06	1	0.26658395	0.33273103
Merch_state_actual/med_1	2.53E-05	3685.35912	2.88800409	21.1034153
Merch_state_actual/toal_1	2.72E-07	1	0.10891857	0.21510139
Merch_state_count_3	1	484	57.2482339	56.330867
Merch_state_avg_3	1.37	28392.84	396.868886	326.841247
Merch_state_max_3	1.37	47900	2685.74154	2965.33838
Merch_state_med_3	1.14	28392.84	192.606537	237.615953
Merch_state_total_3	1.37	324310.24	17518.3917	17714.5644
Merch_state_actual/avg_3	1.75E-05	160.797748	1.01027426	2.33181675
Merch_state_actual/max_3	3.90E-06	1	0.19589952	0.28077769
Merch_state_actual/med_3	2.83E-05	3635.14986	2.94397406	20.4947684
Merch_state_actual/toal_3	1.37E-07	1	0.05663268	0.14424657
Merch_state_count_7	1	789	120.263307	102.897927
Merch_state_avg_7	2.34	27218	394.97386	268.654608

Merch_state_max_7	2.34	47900	3680.55173	3779.48191
Merch_state_med_7	2.3	27218	179.126288	168.188463
Merch_state_total_7	2.34	346823.71	36752.1716	30951.7328
Merch_state_actual/avg_7	1.73E-05	242.503	1.00482106	2.62160633
Merch_state_actual/max_7	1.19E-06	1	0.14534398	0.23119181
Merch_state_actual/med_7	2.79E-05	3567.1123	2.95700086	20.4645861
Merch_state_actual/toal_7	8.95E-08	1	0.02625984	0.08922208
Merch_state_count_14	1	1126	224.688683	185.566031
Merch_state_avg_14	3.62	13696.535	394.21192	229.156736
Merch_state_max_14	3.62	47900	4790.45077	4673.42759
Merch_state_med_14	3.62	13696.535	173.637155	121.711846
Merch_state_total_14	3.62	372690.35	69051.9472	55313.3113
Merch_state_actual/avg_14	1.53E-05	328.249357	1.00718558	2.91705108
Merch_state_actual/max_14	4.42E-07	1	0.11783631	0.20040103
Merch_state_actual/med_14	3.03E-05	3567.1123	2.95672354	20.3673762
Merch_state_actual/toal_14	3.82E-08	1	0.01515421	0.06341682
Merch_state_count_30	1	1901	453.209529	369.012073
Merch_state_avg_30	3.62	5712.488	393.246886	204.529778
Merch_state_max_30	3.62	47900	6391.00485	5820.81607
Merch_state_med_30	3.62	2699.5	169.955141	100.686213
Merch_state_total_30	3.62	522152.48	140259.769	110276.574
Merch_state_actual/avg_30	1.60E-05	339.152004	1.01049944	3.09306134
Merch_state_actual/max_30	4.42E-07	1	0.09259184	0.16951627
Merch_state_actual/med_30	3.36E-05	3567.1123	2.975816	20.4558132
Merch_state_actual/toal_30	2.02E-08	1	0.00870828	0.04697534
day_of_the_week_risk	0.007127	0.02599436	0.01082487	0.00475419