FRAUD ANALYSIS: CREDIT CARD APPLICATION

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Table of Contents

I. Executive Summary

Identity fraud is one of the fastest growing types of white-collar crime in the US. It can be devastating as it can not only affect one's ability to secure credit but also compromise financial history, and in some cases, assets. When an identity is stolen, it usually takes a fair amount of time and money, not to mention a considerable amount of effort, to make sure the fraud is contained, and the victim doesn't suffer any more adverse consequences.

This report provides an analysis of credit card application data for detecting fraud using supervised machine learning methods. We used tools like R, Python, SQL and Microsoft Excel to measure the goodness of our models. Such measures of goodness included, but were not limited to, False Detection Rate (FDR), False Positives, Kolmogorov-Smirnov test (K-S).

The original data set has 94,866 credit card application records. Each entry has 9 variables containing applicants' personal information. An overall view of our analysis is given below.

- ❖ Building expert variables with different time windows
- ❖ Standardization and dimensionality reduction
- ❖ Application fraud algorithm
- ❖ Calculation of measures of goodness

We created a total of 114 variables. Out of 114, we chose 21 expert variables using subset selection methods to apply our supervised learning models. We built various fraud algorithms, such as Linear Regression, Support Vector Machine, Neural Network, Boosted Tree and Bootstrap Forest, and thereby, evaluated their respective fraud detection rates.

Bootstrap Forest model gave us the best results. The model was able to detect present 17.14% of the frauds at 10% (also called, FDR at 10%) in the out-of-time validation data set. Among 15,812 records, 4,061 incidents of fraud were detected.

II. Data Description

Credit card application dataset contains 94,866 entries corresponding to credit card applications. 20,164 of such entries (i.e., 21.26% of the applications) have been marked as fraud. Each record includes information such as name of applicant, address, ZIP code, date of birth, home phone number, date of application and Social Security Number (SSN), as report by the applicant. All variables were masked to conceal the identities of the applicants. The dataset was, however, representative of the applicant pool.

A detailed analysis of the dataset is given below. The Data Quality Report can be found in Appendix.

II.I Data Cleaning and Transformation

II.I.I Correcting DOB

The data only includes observations from 1900 to 1999. However, since the year is denoted by only two digits (YY), it is likely our analysis tools will plug in the wrong century. So, the year 1907 could be interpreted as 2007.

Our first step was to rectify this issue and create a uniform variable that is easy to interpret. Hence, we created a new variable called *newdob*, in which year was denoted using 4 digits (YYYY).

II.I.II Adding Leading Zeros

The observations for variables SSN, ZIP and home phone number had inconsistent lengths. This can be attributed to the fact that computers usually remove leading zeros, and this can make data analysis difficult, especially, when the variables are not quantitative.

To rectify this issue, we added leading zeros to observations corresponding to each of the three variables.

- New variable *newssn* has consistent length of 9 for all its observations
- New variable called *ZIP5* has consistent length of 5 for all its observations
- New variable called *homephone* has consistent length of 10 for all its observations

II.I.III Handling Frivolous

To eliminate the effects of frivolous values, we replaced the affected records in the expert variable with the mean of all the records.

II.I.IV Description of Important Variables

Here is the basic information about our dataset.

Dataset	Personal Identifiable Information (PII)
Records	94,866
Columns	10 categorical variables
Time period	01/01/2016 – 12/31/2016
Resource	Simulated by Professor Stephen Coggeshall

Field Name: *ssn*

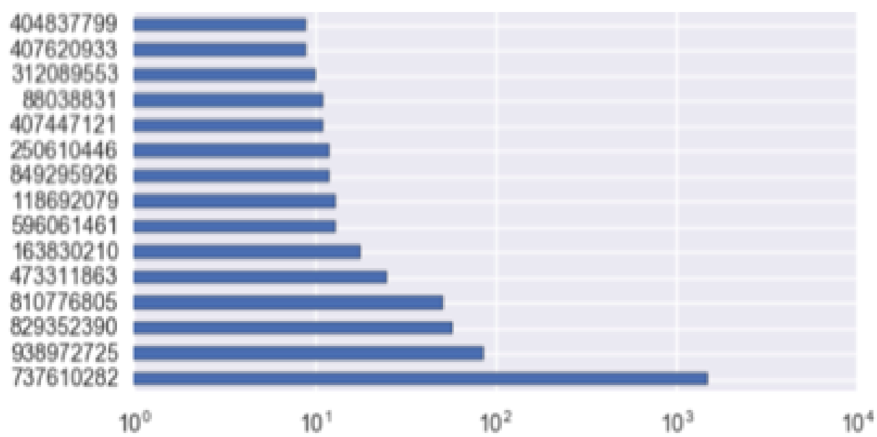
ssn is a categorical variable indicating the applicant's self-reported SSN. This field is 100% populated with 86,711 unique values. An SSN shorter than 9 digits, indicates that there are leading zeros in the observations. For example, a value of '2503' is actually '000002503'. It is obvious that the value '737610282' is frivolous as its frequency is 173 times that of the second most frequently occurring SSN.

15 of the most frequently occurring *ssn* records have been listed below.

ssn	**counts**
737610282	1478
938972725	85
829352390	57
810776805	51
473311863	25
163830210	18

596061461	13
118692079	13
849295926	12
250610446	12
407447121	11
88038831	11
312089553	10
407620933	9
404837799	9

The distributions of the top 15 SSNs is as under.



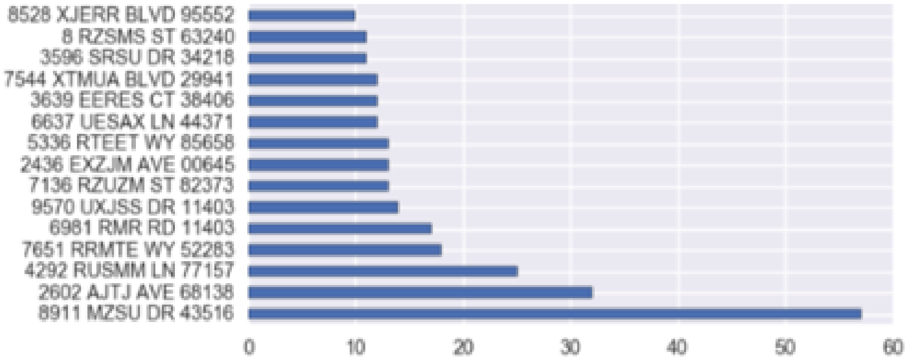
Field Name: *address*

address is a text variable that contains the reported addresses of applicants. The field is 100% populated with 88,167 unique values. The most frequent address '8911 MZSU DR 43516' appeared 57 times. This address is likely to be a frivolous one.

15 of the most frequent addresses have been listed below:

address	counts
8911 MZSU DR 43516	57
2602 AJTJ AVE 68138	32
4292 RUSMM LN 77157	25
7651 RRMTE WY 52283	18
6981 RMR RD 11403	17
9570 UXJSS DR 11403	14
7136 RZUZM ST 82373	13
5336 RTEET WY 85658	13
2436 EXZJM AVE 00645	13
7544 XTMUA BLVD 29941	12
6637 UESAX LN 44371	12
3639 EERES CT 38406	12
3596 SRSU DR 34218	11
8 RZSMS ST 63240	11
8528 XJERR BLVD 95552	10

The distributions of the top 15 records is as under.



Field Name: *zip5*

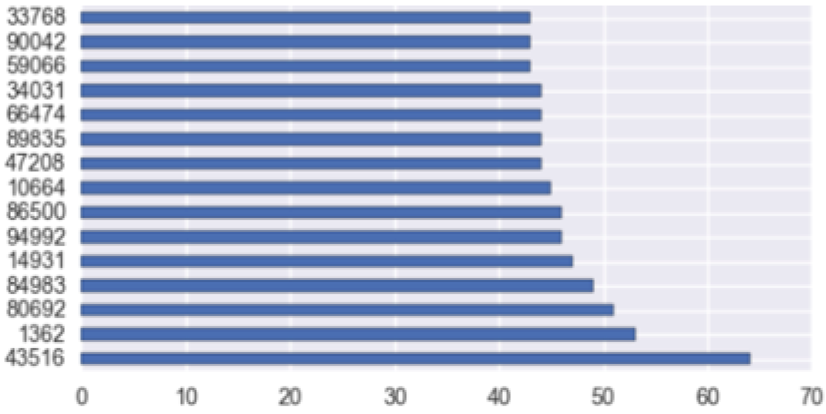
zip5 is a categorical variable that contains ZIP codes of the applicants' neighborhoods. The field is 100% populated with 15,855 unique values. The most frequent zip code, '43516', appeared 64 times. This ZIP code is likely to be a frivolous one.

15 of the most frequently occurring values have been listed below:

zip5	counts
43516	64
1362	53
80692	51
84983	49
14931	47
94992	46
86500	46
10664	45
47208	44
89835	44

66474	44
34031	44
59066	43
90042	43
33768	43

The distributions of the top 15 most frequently occurring ZIP codes is as under.



Field Name: *dob*

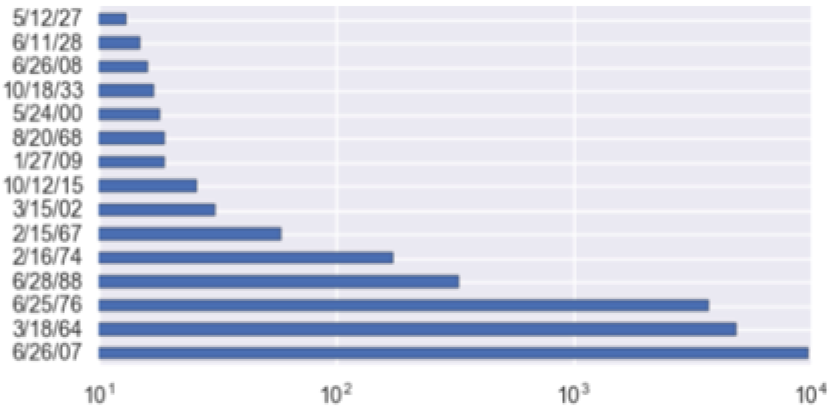
dob is a date variable that contains applicants' reported dates of birth. The field is 100% populated with 30,599 unique values. The most frequent date of birth '*6/26/07*' appeared 9,681 times. This date of birth is likely a frivolous value.

15 of the most frequently occurring values have been listed below.

dob	**counts**
6/26/07	9681
3/18/64	4808
6/25/76	3698

6/28/88	330
2/16/74	173
2/15/67	59
3/15/02	31
10/12/15	26
8/20/68	19
1/27/09	19
5/24/00	18
10/18/33	17
6/26/08	16
6/11/28	15
5/12/27	13

The distributions of the 15 most frequent records are as under.



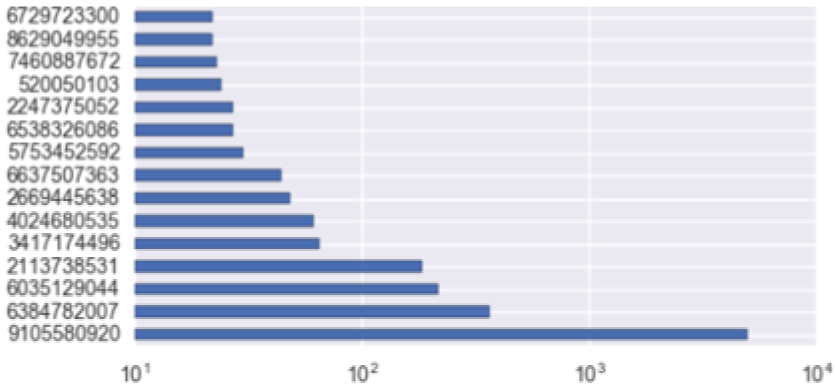
Field Name: *homephone*
homephone is a categorical variable that contains applicants' reported home phone numbers. The field is 100% populated with 22,181 unique values. The most frequent home phone number '*9105580920*' appeared 7,735 times, which accounts for 7.74% of all records. This number is likely a frivolous value.

15 of the most frequently occurring values have been listed below.

homephone	**counts**
9105580920	4974
6384782007	364
6035129044	215
2113738531	184
3417174496	65
4024680535	61
2669445638	48
6637507363	44
5753452592	30
6538326086	27
2247375052	27
520050103	24
7460887672	23
8629049955	22

6729723300	22

The distributions of the 15 most frequent records are as under.



II.II Variable Creation

To make the analysis more in-depth and meaningful, we modified some of the existing variables before we built our expert variables. To create the expert variables, we chose several different time windows corresponding to 1, 3, 5, 7, 14 and 30 days. We chose unique categorical values to compare linkages across the time intervals corresponding to date of birth, SSN, home phone number, ZIP and last name. We ensured that the records took place before the original record by adding a conditional statement to our code specifying that the records being counted had to be less than the original record from which the linkages were drawn. The rationale was to train our models to identify fraudulent applications based on frequencies of certain fields over different time frames.

Using SQL Workbench, we created two identical databases from our original dataset. For every record in the first database, we counted the number of times an earlier record within the given time interval had the same categorical value. In this manner, we created 114 unique expert variables as shown in the table below.

Variables	Description/Formula
same_zip_1	Count of records with same zip within 24 hours before original record.
same_zip_3	Count of records with same zip within three days before original record.
same_zip_5	Count of records with same zip within five days before original record.
same_zip_7	Count of records with same zip within seven days before original record.
same_zip_14	Count of records with same zip within fourteen days before original record.
same_zip_30	Count of records with same zip but different address within thirty days before original record.
same_zip_diff_address_1	Count of records with same zip but different address within 24 hours before original record.
same_zip_diff_address_3	Count of records with same zip but different address within three days before original record.
same_zip_diff_address_5	Count of records with same zip but different address within five days before original record.
same_zip_diff_address_7	Count of records with same zip but different address within seven days before original record.
same_zip_diff_address_14	Count of records with same zip but different address within fourteen days before original record.
same_zip_diff_address_30	Count of records with same zip but different address within thirty days before original record.
same_zip_diff_ssn_1	Count of records with same zip but different ssn within 24 hours before original record.
same_zip_diff_ssn_3	Count of records with same zip but different ssn within three days before original record.
same_zip_diff_ssn_5	Count of records with same zip but different ssn within five days before original record.
same_zip_diff_ssn_7	Count of records with same zip but different ssn within seven days before original record.
same_zip_diff_ssn_14	Count of records with same zip but different ssn within fourteen days before original record.
same_zip_diff_ssn_30	Count of records with same zip but different ssn within thirty days before original record.
same_zip_diff_dob_1	Count of records with same zip but different DOB within 24 hours before original record.
same_zip_diff_dob_3	Count of records with same zip but different DOB within three days before original record.
same_zip_diff_dob_7	Count of records with same zip but different DOB within seven days before original record.
same_zip_diff_dob_5	Count of records with same zip but different DOB within five days before original record.
same_zip_diff_dob_14	Count of records with same zip but different DOB within fourteen days before original record.
same_zip_diff_dob_30	Count of records with same zip but different DOB within thirty days before original record.
same_phone_diff_phone_1	Count of records with same zip but different phone number within 24 hours before original record.
same_zip_diff_phone_3	Count of records with same zip but different phone number within three days before original record.
same_zip_diff_phone_7	Count of records with same zip but different phone number within seven days before original record.
same_zip_diff_phone_5.x	Count of records with same zip but different phone number within five days before original record.
same_zip_diff_phone_14	Count of records with same zip but different phone number within fourteen days before original record.
same_zip_diff_phone_30	Count of records with same zip but different phone number within thirty days before original record.
same_ssn_1	Count of records with same SSN within 24 hours before original record.
same_ssn_3	Count of records with same SSN within three days before original record.
same_ssn_5	Count of records with same SSN within five days before original record.
same_ssn_7	Count of records with same SSN within seven days before original record.
same_ssn_14	Count of records with same SSN within fourteen days before original record.
same_ssn_30	Count of records with same SSN within thirty days before original record.
same_ssn_diff_address_1	Count of records with same SSN but different address within 24 hours before original record.
same_ssn_diff_address_3	Count of records with same SSN but different address within three days before original record.
same_ssn_diff_address_5	Count of records with same SSN but different address within five days before original record.
same_ssn_diff_address_7	Count of records with same SSN but different address within seven days before original record.
same_ssn_diff_address_14	Count of records with same SSN but different address within fourteen days before original record.
same_ssn_diff_address_30	Count of records with same SSN but different phone number within thirty days before original record.
same_ssn_diff_phone_1	Count of records with same SSN but different phone number within 24 hours before original record.
same_ssn_diff_phone_3	Count of records with same SSN but different phone number within three days before original record.
same_ssn_diff_phone_5	Count of records with same SSN but different phone number within five days before original record.
same_ssn_diff_phone_7	Count of records with same SSN but different phone number within seven days before original record.
same_ssn_diff_phone_14	Count of records with same SSN but different phone number within fourteen days before original record.
same_ssn_diff_phone_30	Count of records with same SSN but different phone number within thirty days before original record.
same_ssn_diff_dob_1	Count of records with same SSN but different DOB within 24 hours before original record.
same_ssn_diff_dob_3	Count of records with same SSN but different DOB within three days before original record.
same_ssn_diff_dob_5	Count of records with same SSN but different DOB within five days before original record.
same_ssn_diff_dob_7	Count of records with same SSN but different DOB within seven days before original record.
same_ssn_diff_dob_14	Count of records with same SSN but different DOB within fourteen days before original record.
same_ssn_diff_dob_30	Count of records with same SSN but different DOB within thirty days before original record.
same_ssn_diff_zip_1	Count of records with same SSN but different zip within 24 hours before original record.
same_ssn_diff_zip_3	Count of records with same SSN but different zip within three days before original record.
same_ssn_diff_zip_5	Count of records with same SSN but different zip within five days before original record.

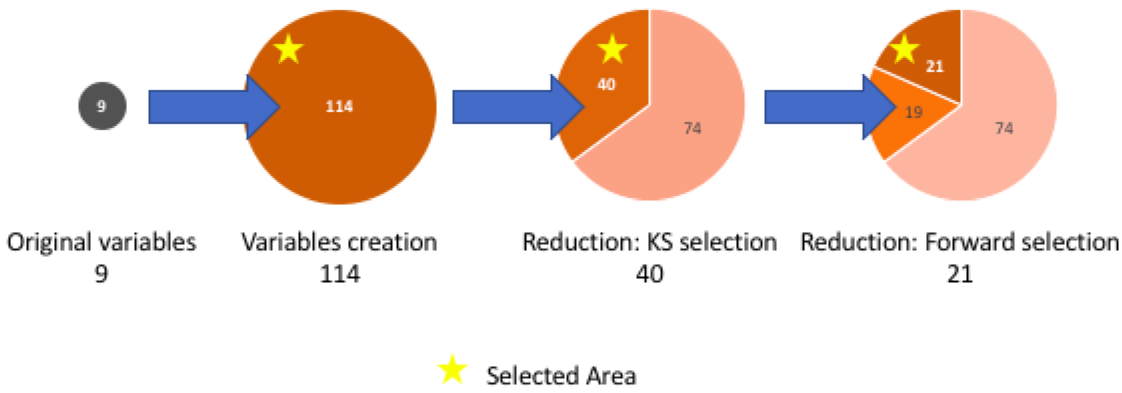
Variables	Description/Formula
same_ssn_diff_zip_7	Count of records with same SSN but different zip within seven days before original record.
same_ssn_diff_zip_14	Count of records with same SSN but different zip within fourteen days before original record.
same_ssn_diff_zip_30	Count of records with same SSN but different zip within thirty days before original record.
same_phone_1	Count of records with same phone number within 24 hours before original record.
same_phone_3	Count of records with same phone number within three days before original record.
same_phone_5	Count of records with same phone number within five days before original record.
same_phone_7	Count of records with same phone number within seven days before original record.
same_phone_14	Count of records with same phone number within fourteen days before original record.
same_phone_30	Count of records with same phone number within thirty days before original record.
same_phone_diff_address_1	Count of records with same phone number but different address within 24 hours before original record.
same_phone_diff_address_3	Count of records with same phone number but different address within three days before original record.
same_phone_diff_address_5	Count of records with same phone number but different address within five days before original record.
same_phone_diff_address_7	Count of records with same phone number but different address within seven days before original record.
same_phone_diff_address_14	Count of records with same phone number but different address within fourteen days before original record.
same_phone_diff_address_30	Count of records with same phone number but different address within thirty days before original record.
same_phone_diff_ssn_1	Count of records with same phone number but different SSN within 24 hours before original record.
same_phone_diff_ssn_3	Count of records with same phone number but different SSN within three days before original record.
same_phone_diff_ssn_5	Count of records with same phone number but different SSN within five days before original record.
same_phone_diff_ssn_7	Count of records with same phone number but different SSN within seven days before original record.
same_phone_diff_ssn_14	Count of records with same phone number but different SSN within fourteen days before original record.
same_phone_diff_ssn_30	Count of records with same phone number but different SSN within thirty days before original record.
same_phone_diff_dob_1	Count of records with same phone number but different DOB within before original record.
same_phone_diff_dob_3	Count of records with same phone number but different DOB within three days before original record.
same_phone_diff_dob_5	Count of records with same phone number but different DOB within before original record.
same_phone_diff_dob_7	Count of records with same phone number but different DOB within seven days before original record.
same_phone_diff_dob_14	Count of records with same phone number but different DOB within fourteen days before original record.
same_phone_diff_dob_30	Count of records with same phone number but different DOB within thirty days before original record.
same_phone_diff_zip_1	Count of records with same phone number but different zip within 24 hours before original record.
same_phone_diff_zip_3	Count of records with same phone number but different zip within three days before original record.
same_phone_diff_zip_7	Count of records with same phone number but different zip within seven days before original record.
same_phone_diff_zip_5	Count of records with same phone number but different zip within five days before original record.
same_phone_diff_zip_14	Count of records with same phone number but different zip within fourteen days before original record.
same_phone_diff_zip_30	Count of records with same phone number but different zip within thirty days before original record.
same_nameDOB_1	Count of records with same last name and DOB within 24 hours before original record.
same_nameDOB_3	Count of records with same last name and DOB within three days before original record.
same_nameDOB_5	Count of records with same last name and DOB within five days before original record.
same_nameDOB_7	Count of records with same last name and DOB within seven days before original record.
same_nameDOB_14	Count of records with same last name and DOB within fourteen days before original record.
same_nameDOB_30	Count of records with same last name and DOB within thirty days before original record.
same_nameDOB_diff_address_1	Count of records with same last name and DOB but different address within 24 hours before original record.
same_nameDOB_diff_address_3	Count of records with same last name and DOB but different address within three days before original record.
same_nameDOB_diff_address_5	Count of records with same last name and DOB but different address within five days before original record.
same_nameDOB_diff_address_7	Count of records with same last name and DOB but different address within seven days before original record.
same_nameDOB_diff_address_14	Count of records with same last name and DOB but different address within fourteen days before original record.
same_nameDOB_diff_address_30	Count of records with same last name and DOB but different address within thirty days before original record.
same_nameDOB_diff_ssn_1	Count of records with same last name and DOB but different SSN within 24 hours before original record.
same_nameDOB_diff_ssn_3	Count of records with same last name and DOB but different SSN within three days before original record.
same_nameDOB_diff_ssn_5	Count of records with same last name and DOB but different SSN within five days before original record.
same_nameDOB_diff_ssn_7	Count of records with same last name and DOB but different SSN within seven days before original record.
same_nameDOB_diff_ssn_14	Count of records with same last name and DOB but different SSN within fourteen days before original record.
same_nameDOB_diff_ssn_30	Count of records with same last name and DOB but different SSN within thirty days before original record.
same_nameDOB_diff_phone_1	Count of records with same last name and DOB but different phone number within 24 hours before original record.
same_nameDOB_diff_phone_3	Count of records with same last name and DOB but different phone number within three days before original record.
same_nameDOB_diff_phone_7	Count of records with same last name and DOB but different phone number within seven days before original record.
same_nameDOB_diff_phone_5	Count of records with same last name and DOB but different phone number within before original record.
same_nameDOB_diff_phone_14	Count of records with same last name and DOB but different phone number within fourteen days before original record.
same_nameDOB_diff_phone_30	Count of records with same last name and DOB but different phone number within thirty days before original record.

III. Feature Selection

Feature selection has multiplicative effects on the overall modeling process.

- **Reduces overfitting**: Less redundant data means less opportunity to make decisions based on noise
- **Improves accuracy**: Less misleading data means modeling accuracy improves
- **Reduces training time**: Less data means that algorithms train faster

We used filter feature selection (Kolmogorov–Smirnov test) and wrapper feature selection (forward selection) to identify the most valuable variables for our modeling. We selected 40 variables after Kolmogorov–Smirnov and from that, we selected 21 variables by forward selection. An illustration shown below summarizes the feature selection process.



III.I Filter Feature Selection

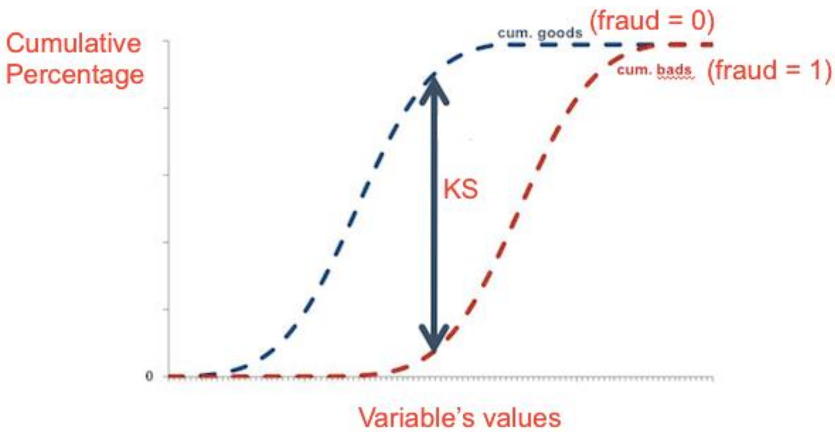
Kolmogorov–Smirnov score can be used in filter feature selection to measure the ability of one variable to distinguish classes. In statistics, the Kolmogorov–Smirnov test (K–S test) is a nonparametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution (one-sample K–S test), or to compare two samples (two-sample K–S test).

We implemented Kolmogorov–Smirnov using Python in the following steps:

- For each variable, we calculated the cumulative percentage on every variable's class i.e., good (*fraud* = 0) and bad (*fraud* = 1) separately, so we get two cumulative distributions.
- For each variable, we used *stats.ks_2samp()* function from *spicy* package in Python to calculate the K-S between distributions of good (*fraud* = 0) and bad (*fraud* = 1) records.

- Finally, we sorted variables by decreasing K-S and chose the first 40 variables for the next step.

An illustration of K-S is as under.

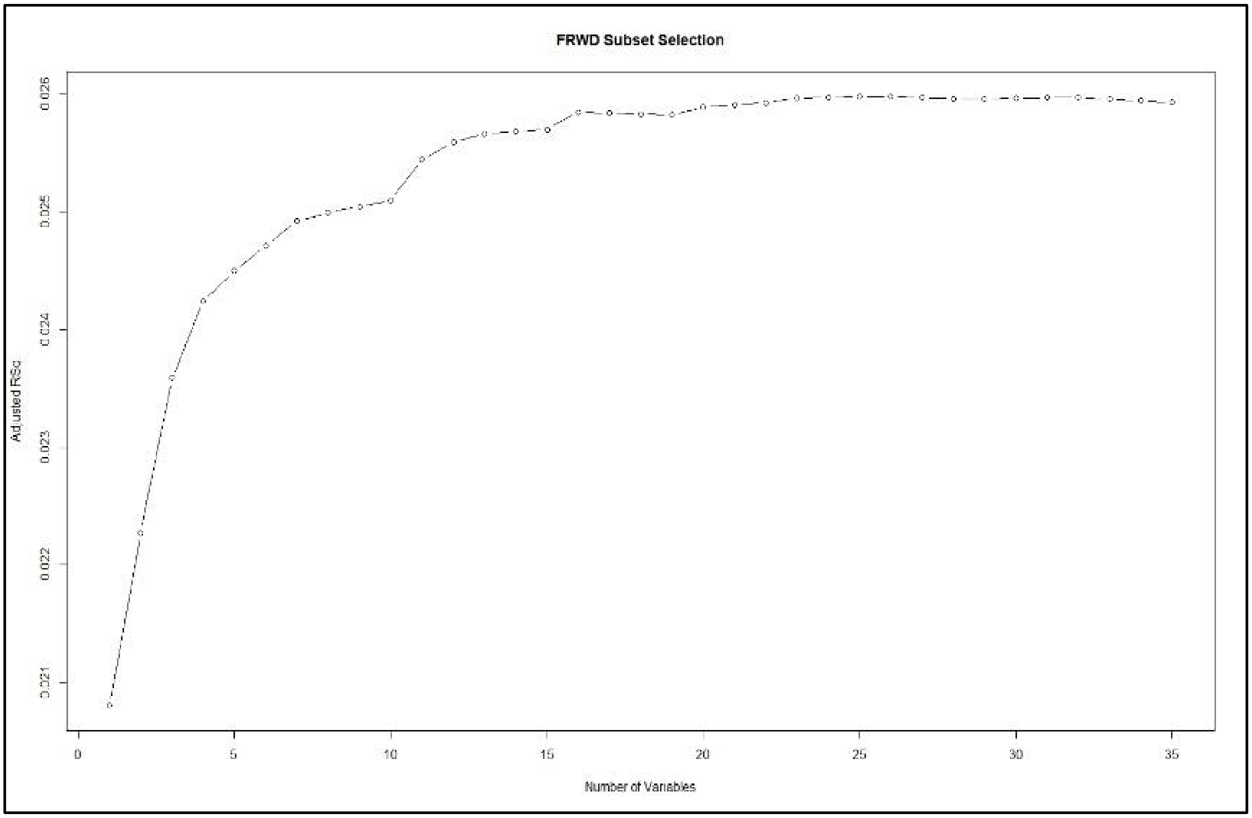


III.II Wrapper Feature Selection

Forward selection is one of the wrapper feature selection methods. It may be noted here that filter methods pick up the intrinsic properties of the features (i.e., the relevance of the features) measured via univariate statistics instead of cross-validation performance, whereas wrapper methods essentially optimize the classifier performance. Wrapper methods are computationally more expensive compared to filter methods due to the repeated learning steps and cross-validation.

The simplest data-driven model building approach is called forward selection. In this approach, one adds variables to the model one at a time. At each step, each variable that is not already in the model is tested for inclusion in the model. And then, we use adjusted R^2 to judge goodness of model with different number of variables. Based on forward selection, we found that model performance is optimal when the number of variables is 21. These variables were selected for model building.

A plot of number of variables versus adjusted R^2 (forward subset selection) has been given below.



IV. Algorithms

After creating expert variables, we did standardization and dimensionality reduction. Subsequently, we calculated the fraud detection rate at 10% for various supervised learning algorithms. The results have been summarized in the following table.

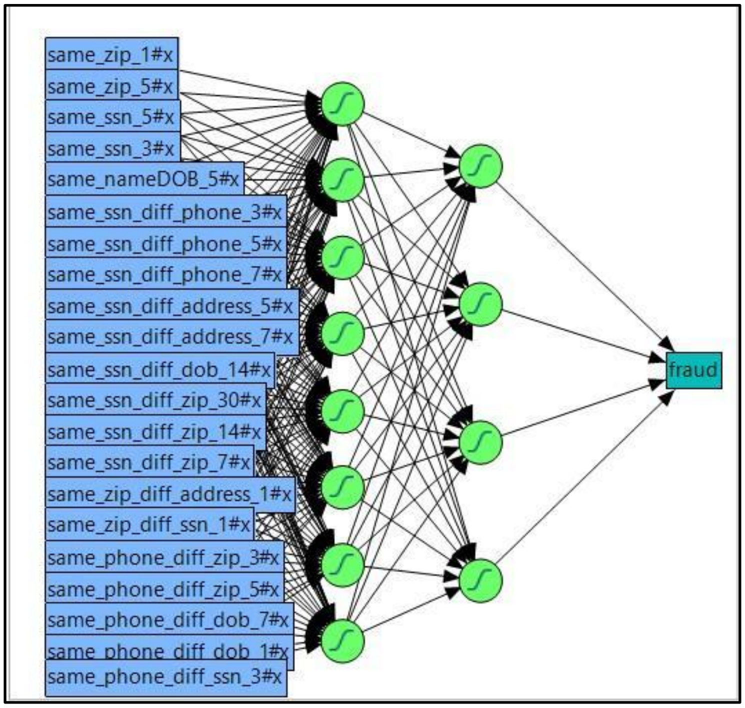
FDR @ 10%			
Model	Training	Testing	Out of Time
SVM	14.48%	14.20%	13.03%
Linear Regression	18.91%	18.19%	15.64%
Neural Network	19.22%	18.30%	15.96%
Boosted Tree	19.46%	18.42%	16.87%
Bootstrap Forest	19.60%	18.98%	17.14%

IV.I Description of Algorithms

i. Support Vector Machine: It's a supervised learning model with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

ii. Linear Regression: Linear regression is a statistical modeling technique used to describe a continuous response variable as a linear function of one or more predictor variables.

iii. Neural Network: It is a technique in which while learning, one of the input patterns is given to the net's input layer. This pattern is propagated through the net (independent of its structure) to the net's output layer. The output layer generates an output pattern which is then compared to the target pattern. A depiction of our neural network model has been shown below.



iv. Boosted Tree: It is a technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

v. Bootstrap Forest: It is an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification), or mean prediction (regression) of the individual trees.

IV.II Measures of Goodness for Fraud Models

Kolmogorov–Smirnov Test (K-S test): It is a nonparametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution (one-sample K–S test), or to compare two samples (two-sample K–S test).

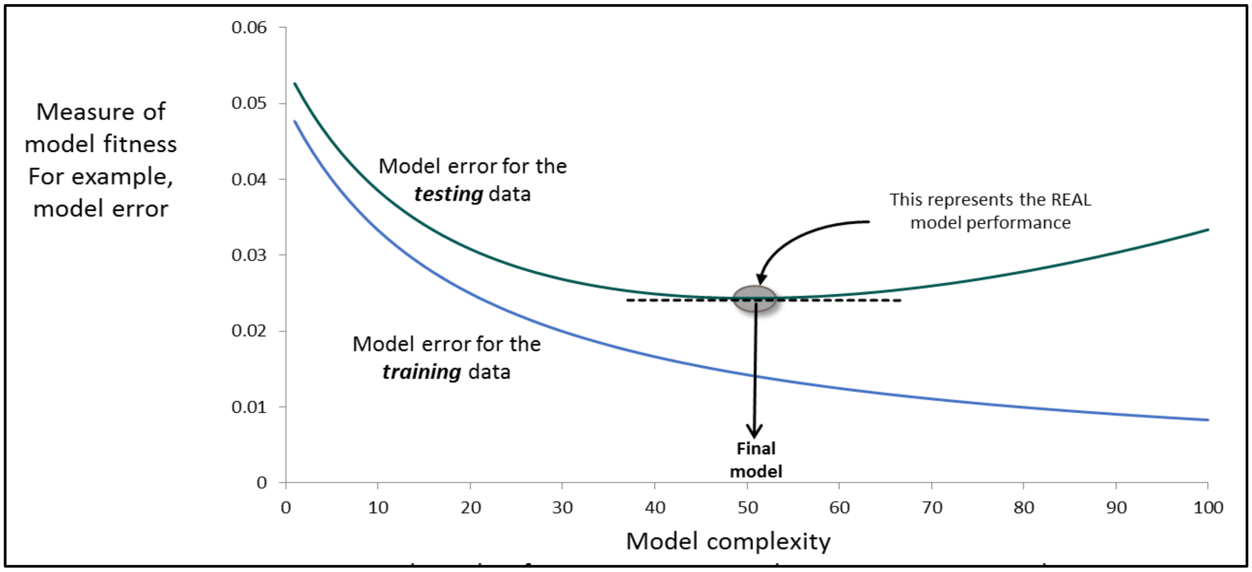
Fraud Detection Rate (FDR): It is measure of goodness wherein we evaluate what percentage of all the frauds that are caught at a cutoff location. For instance, an FDR of 50% at 10% means the model catches 50% of all the frauds in 10% of the population.

False Positive: A false positive error, or in short, a false positive, commonly called a "false alarm", is a result that indicates a given condition exists when it does not.

IV.III Out of Time Model Validation

We separated the data into multiple sets to ensure that our models are robust. We build the model on the training data (equivalent to 6 months' worth of data), then evaluated it on the testing data (equivalent to 4 months' worth of data). In addition to that, we also reserved a set of data (corresponding to applications during Nov-Dec, 2016) that was never used during training. In other words, it was a data set that our models had never seen before. Validation on this holdout sample is called out-of-time validation.

An illustration about optimal model performance has been given below. Out-of-time validation goes a step further and tests the robustness of the model once again.

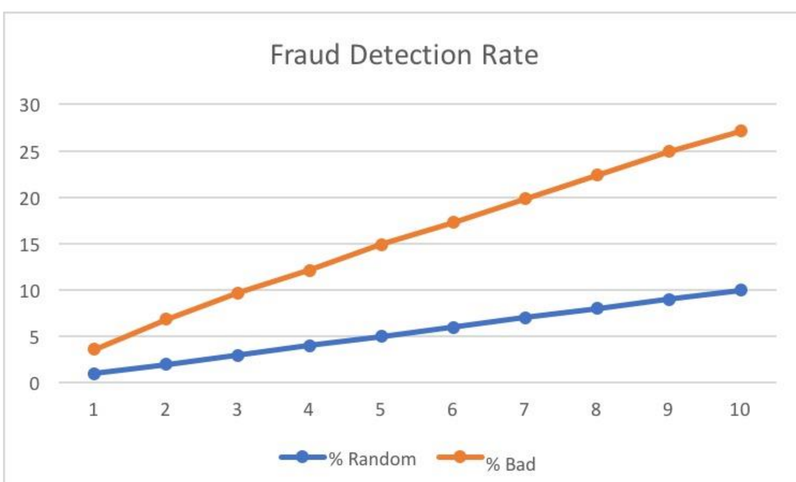


V. Results

In this section we provide an overview of our results. We plot the score distributions as well as create a table of the top 25% bins.

	Bin Statistic					Cumulative Satistics(Bootstrap Forest Model)					
Population Bin %	Total # record	#BAD	#GOOD	%BAD	%GOOD	Cumulative Bad	Cumulative Good	% Bad(FDR)	% Good	KS	False Pos. Ratio
1	158	35	123	0.221519	0.778481	106	52	2.610195	0.442516	2.167679	0.490566
2	158	36	122	0.227848	0.772152	196	120	4.826397	1.021190	3.805208	0.612245
3	158	45	113	0.284810	0.715190	272	202	6.697858	1.719003	4.978855	0.742647
4	158	39	119	0.246835	0.753165	331	301	8.150702	2.561484	5.589218	0.909366
5	158	50	108	0.316456	0.683544	402	388	9.899040	3.301847	6.597193	0.965174
6	158	42	116	0.265823	0.734177	459	489	11.302635	4.161348	7.141287	1.065359
7	158	43	115	0.272152	0.727848	521	585	12.829352	4.978300	7.851053	1.122841
8	158	38	120	0.240506	0.759494	583	681	14.356070	5.795251	8.560818	1.168096
9	158	45	113	0.284810	0.715190	646	776	15.907412	6.603693	9.303719	1.201238
10	158	45	113	0.284810	0.715190	696	884	17.138636	7.522764	9.615872	1.270115
11	158	34	124	0.215190	0.784810	757	981	18.640729	8.348226	10.292503	1.295905
12	158	48	110	0.303797	0.696203	820	1076	20.192071	9.156668	11.035403	1.312195
13	158	36	122	0.227848	0.772152	886	1168	21.817286	9.939580	11.877707	1.318284
14	158	36	122	0.227848	0.772152	938	1274	23.097759	10.841631	12.256129	1.358209
15	158	39	119	0.246835	0.753165	1007	1363	24.796848	11.599013	13.197835	1.353525
16	158	47	111	0.297468	0.702532	1065	1463	26.225068	12.450004	13.775063	1.373709
17	158	43	115	0.272152	0.727848	1108	1578	27.283920	13.428644	13.855276	1.424188
18	158	53	105	0.335443	0.664557	1147	1697	28.244275	14.441324	13.802951	1.479512
19	158	42	116	0.265823	0.734177	1179	1823	29.032258	15.513573	13.518685	1.546226
20	158	43	115	0.272152	0.727848	1203	1957	29.623246	16.653902	12.969344	1.626766
21	158	35	123	0.221519	0.778481	1225	2093	30.164984	17.811250	12.353734	1.708571
22	158	30	128	0.189873	0.810127	1257	2219	30.952967	18.883499	12.069468	1.765314
23	158	32	126	0.202532	0.797468	1298	2336	31.962571	19.879159	12.083412	1.799692
24	158	41	117	0.259494	0.740506	1332	2460	32.799803	20.934389	11.865414	1.846847
25	158	39	119	0.246835	0.753165	1371	2579	33.760158	21.947068	11.813089	1.881109

Among 15,812 records in our out-of-time holdout sample, our best model, Bootstrap Forest, detected 11,751 good ones (*fraud* = 0) and 4,061 bad ones (*fraud* = 1).



VI. Conclusions

In this project we started with exploratory analysis of the data which included descriptive analysis and visualization. Next, we cleaned and transformed the original credit card application dataset and created new variables so that we could create various supervised learning algorithms with the aim of detecting fraudulent applications.

After evaluating various algorithms, like Support Vector Machine, Neural Network, Boosted Tree, Linear Regression and Bootstrap Forest, we found that **Bootstrap Forest algorithm gave the best results with an FDR of 17.14% at 10%**, which is to say that the model catches 17.14% of all frauds in 10% of the population.

VI.I Scope for Improvement

There are several things that can be done to improve our models. Some have been listed below.

i. Domain Expertise: The final model can be improved by inputs from experts. We can think of creating better variables to better capture information and improve the accuracy of our models.

ii. Augmenting Data: If we can get more information about credit card applications it may be useful in improving the model further.

iii. Comparison with Historic Data: It's a good idea to look at how fraud detection is applied in other areas and see what new ideas can be incorporated in our models. This might help in uncovering some new ideas and attributes which can further improve the model.

VII. Appendix

VII.I Data Quality Report

BASIC INFORMATION

Dataset	Personal Identifiable Information (PII)
Records	94,866
Columns	10 categorical variables
Time period	01/01/2016 – 12/31/2016
Resource	Simulated by Professor Stephen Coggeshall

SUMMARY TABLE

Type	Variables	# of Unique values	Count	Percentage populated
Categorical	record	94,899	94,866	100%
	date	365	94,866	100%
	ssn	86,771	94,866	100%
	firstname	14,626	94,866	100%
	lastname	31,513	94,866	100%
	address	88,167	94,866	100%
	zip5	15,855	94,866	100%
	dob	30,599	94,866	100%
	homephone	20,762	94,866	100%
	fraud	2	94,866	100%

DATA ANALYSIS

record – order number of each record

Number of values: 94,866

Number of unique values: 94,899

Distribution: Starts from 1, increasing by 1 each time, with no repetition.

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date – date of generating records

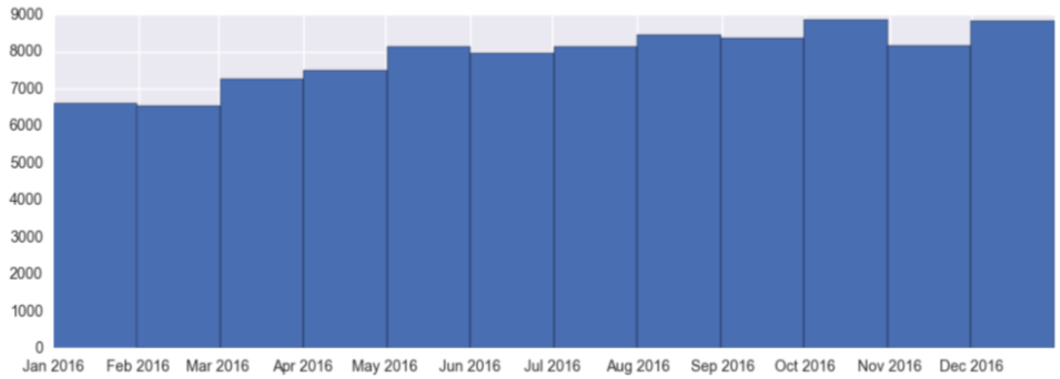
Number of values: 94,866

Number of unique values: 356

Top 15 values:

rank	date	counts
1	06/09/16	329
2	12/29/16	328
3	11/19/16	325
4	09/18/16	324
5	10/18/16	324
6	10/02/16	320
7	12/10/16	320
8	12/08/16	320
9	10/07/16	320
10	12/30/16	319
11	08/27/16	315
12	12/31/16	307
13	09/25/16	306
14	10/21/16	305
15	09/15/16	305

Monthly distribution:



ssn – social security number of each record

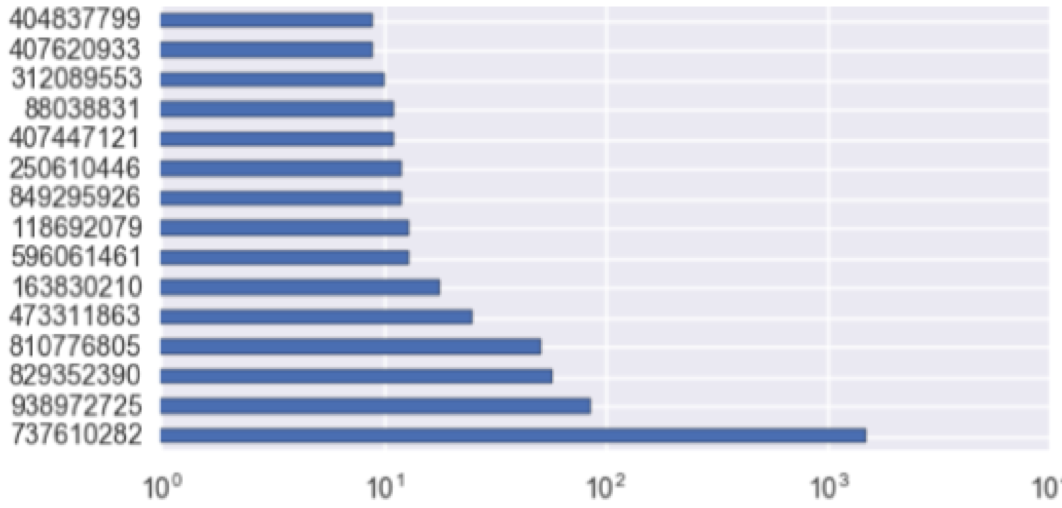
Number of values: 94,866

Number of unique values: 86,771

Top 15 values:

rank	ssn	counts
1	737610282	1478
2	938972725	85
3	829352390	57
4	810776805	51
5	473311863	25
6	163830210	18
7	596061461	13
8	118692079	13
9	849295926	12
10	250610446	12
11	407447121	11
12	88038831	11
13	312089553	10
14	407620933	9
15	404837799	9

Log scale bar chart of top 15 values:



firstname – first name of each record

Number of values: 94,866

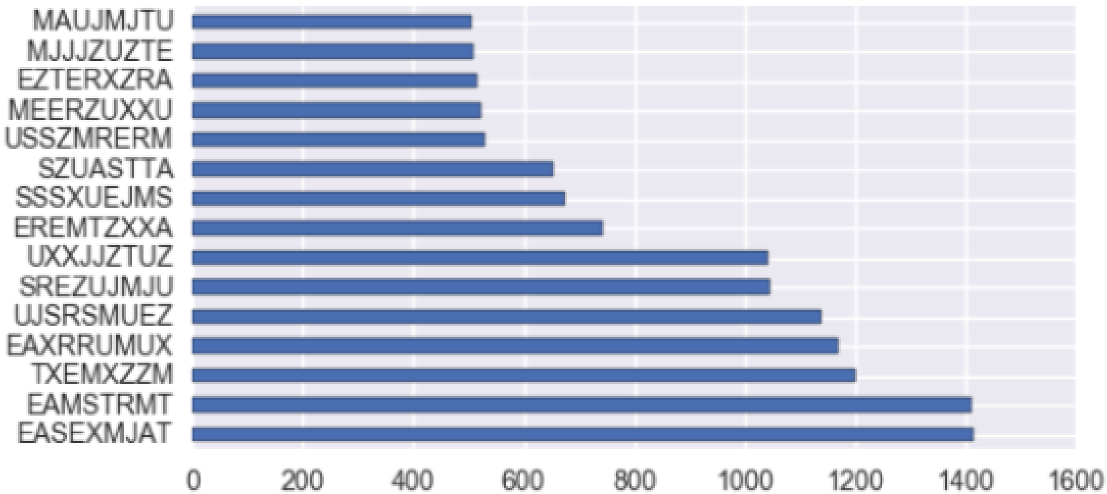
Number of unique values: 14,626

Top 15 values:

rank	firstname	counts
1	EASEXMJAT	1414

2	EAMSTRMT	1411
3	TXEMXZZM	1200
4	EAXRRUMUX	1170
5	UJSRSMUEZ	1138
6	SREZUJMJU	1044
7	UXXJJZTUZ	1042
8	EREMTZXXA	742
9	SSSXUEJMS	675
10	SZUASTTA	653
11	USSZMRERM	529
12	MEERZUXXU	523
13	EZTERXZRA	516
14	MJJJZUZTE	510
15	MAUJMJTU	504

Bar chart of top 15 values:



lastname - last name of each record

Number of values: 94,866

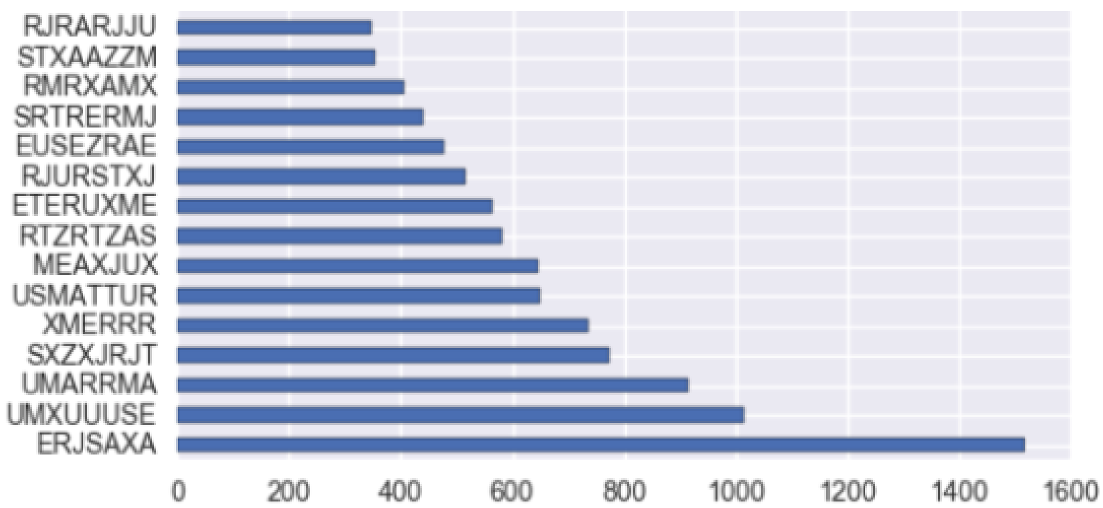
Number of unique values: 31,513

Top 15 values:

rank	lastname	counts
1	ERJSAXA	1515
2	UMXUUUSE	1013

3	UMARRMA	913
4	SXZXJRJT	775
5	XMERRR	737
6	USMATTUR	649
7	MEAXJUX	645
8	RTZRTZAS	582
9	ETERUXME	562
10	RJURSTXJ	515
11	EUSEZRAE	476
12	SRTRERMJ	438
13	RMRXAMX	405
14	STXAAZZM	352
15	RJRARJJU	348

Bar chart of top 15 values:



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address - address of each record

Number of values: 94,866

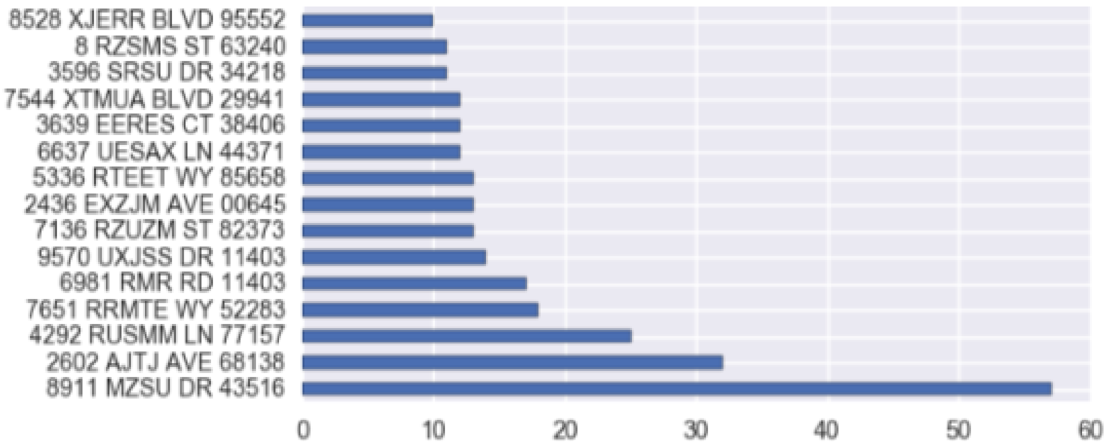
Number of unique values: 88,167

Top15 values:

rank	address	counts
1	8911 MZSU DR 43516	57
2	2602 AJTJ AVE 68138	32

3	4292 RUSMM LN 77157	25
4	7651 RRMTE WY 52283	18
5	6981 RMR RD 11403	17
6	9570 UXJSS DR 11403	14
7	7136 RZUZM ST 82373	13
8	5336 RTEET WY 85658	13
9	2436 EXZJM AVE 00645	13
10	7544 XTMUA BLVD 29941	12
11	6637 UESAX LN 44371	12
12	3639 EERES CT 38406	12
13	3596 SRSU DR 34218	11
14	8 RZSMS ST 63240	11
15	8528 XJERR BLVD 95552	10

Bar chart of TOP 15 values:



zip5 – zip code of each record

Number of values: 94,866

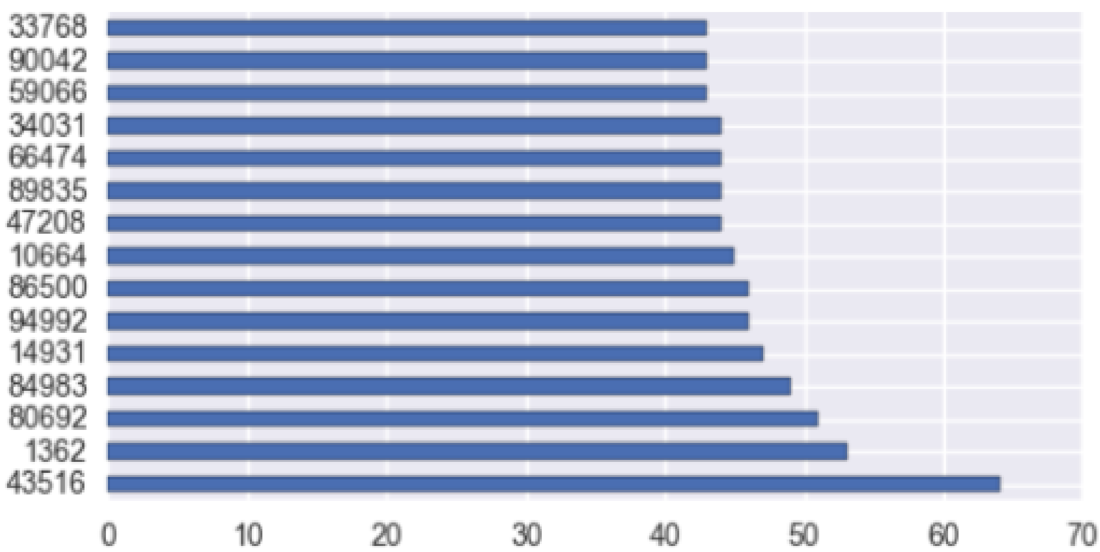
Number of unique values: 15,855

Top15 values:

rank	zip5	counts
1	43516	64
2	1362	53
3	80692	51
4	84983	49
5	14931	47

6	94992	46
7	86500	46
8	10664	45
9	47208	44
10	89835	44
11	66474	44
12	34031	44
13	59066	43
14	90042	43
15	33768	43

Bar chart of TOP 15 values:



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dob – date of birth of each record

Number of values: 94,866

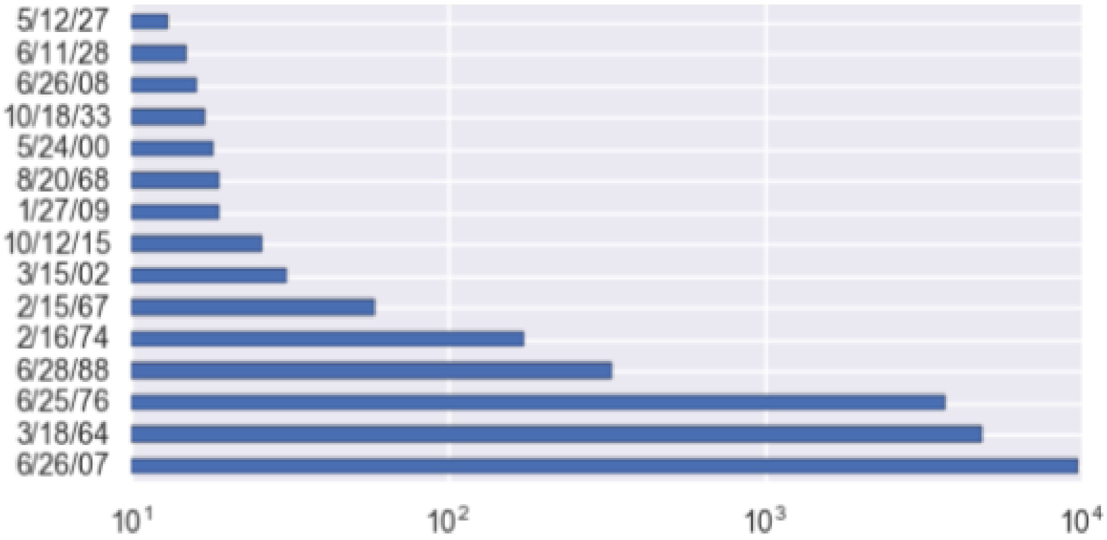
Number of unique values: 30,599

Top 15 values:

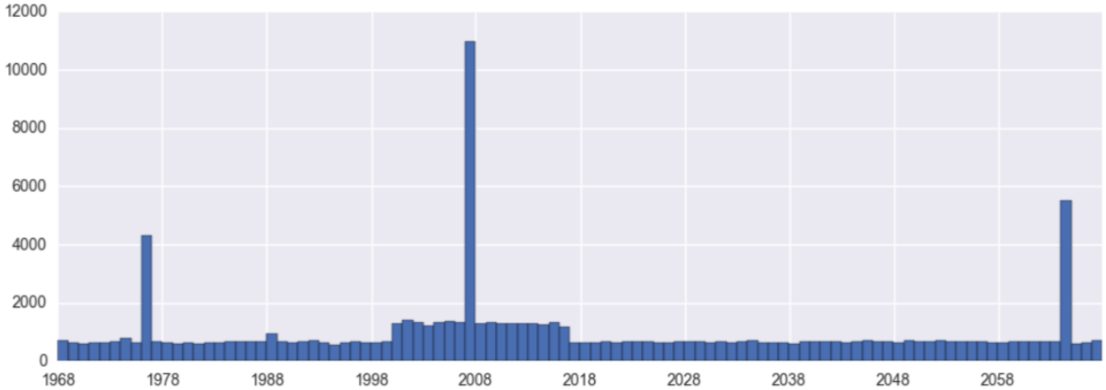
rank	dob	counts
1	6/26/07	9681
2	3/18/64	4808
3	6/25/76	3698
4	6/28/88	330

5	2/16/74	173
6	2/15/67	59
7	3/15/02	31
8	10/12/15	26
9	8/20/68	19
10	1/27/09	19
11	5/24/00	18
12	10/18/33	17
13	6/26/08	16
14	6/11/28	15
15	5/12/27	13

Bar chart of top 15 values:



Yearly distribution:



homephone – home phone number of each record

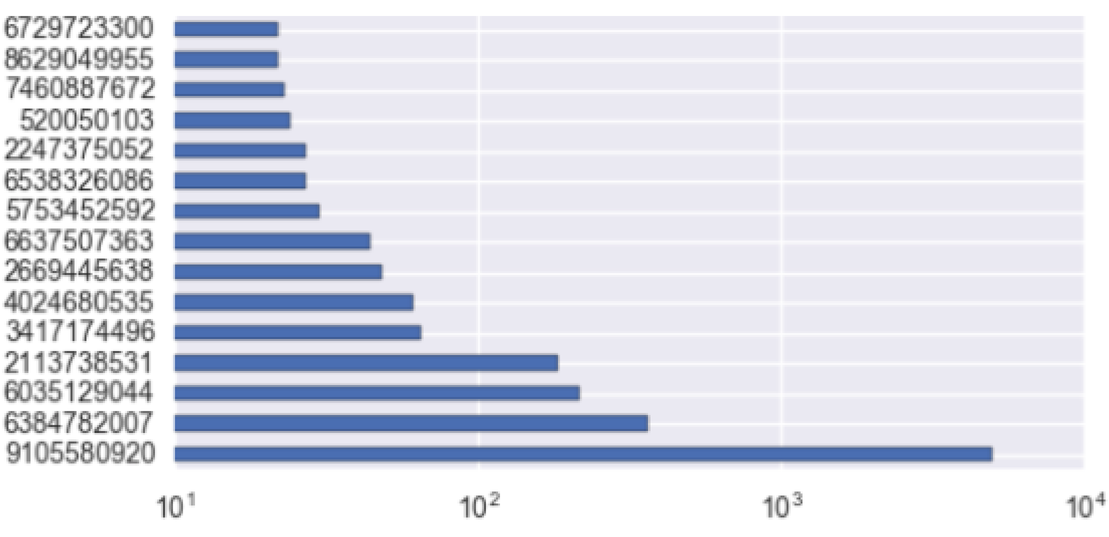
Number of values: 94,866

Number of unique values: 20,762

Top 15 values:

rank	homephone	counts
1	9105580920	4974
2	6384782007	364
3	6035129044	215
4	2113738531	184
5	3417174496	65
6	4024680535	61
7	2669445638	48
8	6637507363	44
9	5753452592	30
10	6538326086	27
11	2247375052	27
12	520050103	24
13	7460887672	23
14	8629049955	22
15	6729723300	22

Bar chart of TOP 15 values:



fraud – judgement of each record, whether it is fraud or not

Number of values: 94,866

Number of unique values: 2

Values distribution:

Rank	fraud	counts	percentage
1	0	70702	78.7%
2	1	20164	21.3%

1 means fraud, so 21.3% of records are fraud.

FURTHER ANALYSIS

Number of transactions monthly versus semimonthly versus weekly versus daily