# Application Fraud Detection

A Report on Building a Supervised Machine Learning Model on Credit Product Application Data

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## Executive Summary

This project focuses on using advanced analytical modeling and techniques to find identity fraud. Identity fraud is the act of misrepresenting who you are in order to improperly receive services or to remain “hidden” while conducting illegal activity. There are three core methods of identity fraud: identity theft, identity manipulation, and using synthetic identity. Our goal was to use only identity fields to build a model for flagging potential application/identity fraud in real time.

Our dataset was synthetic generated from analysis of over one billion real US applications over a ten year period. The data was created to attempt to mimic real application data and contained over one million records with various personally identifiable information fields including social security number, first and last name, address, date of birth, and home phone number.

We started by cleaning the data set of any frivolous fields, common values used to fill missing fields, and replaced them with unique values. We created over 350 candidate variables by linking applications through different combinations of identity fields. These candidate variables included a risk table for the day of the week, days since last seen for a specific attribute, velocity which captures the number of times an attribute appears in the past n days, and relative velocity, a ratio between recent occurrences and longer time periods for an attribute.

In order to prepare our dataset for model building, we used a filter and wrapper feature selection process to reduce the total number of variables. First, we ran a filter, which selected the variables with the highest average KS and FDR rank. Next, we used RFECV, a backward selection wrapper, to rank and narrow our field of variables. Lastly, we ran RFE, without cross validation, to get a well-ranked list of 30 different candidate variables.

Using our 30 most-important variables, we created 43 unique models from four different binary classification algorithms: Logistic Regression, Random Forest, XGBoost, and Neural Networks. Each of these models used an unique combination of sampling strategies and hyperparameters. Based on the best performance on the test set, we selected XGBoost, a gradient boosting algorithm, as our final model with 600 estimators, a max depth of 3 for each estimator, a learning rate of 0.1, and a subsample ratio of 0.8. This model produced a fraud detection rate for 3% of the population at 53.56%. The success of our final model demonstrates a real business opportunity to implement our solution as an effective way of catching identity fraud.

# Description of Data

Our dataset was synthetically generated from analysis of over one billion real credit card and cell phone applications over a ten year period. This data contained one million records within a one year time period, from January 1st, 2016 to December 31st, 2016. There are a total of ten unique fields containing identity information like social security number, applicant's name, address, homephone, and date of birth. Each record had a fraud label with 1 flagging an application as identity fraud and 0 representing a normal application. Below is a summary table detailing the percent of fields populated, the number of unique values, and the most common field value.

| Column Name | # Records | % Populated | Unique Values | Min | Max | Most Common Field Value |
|---|---|---|---|---|---|---|
| record | 1,000,000 | 100 | 1000000 | N/A | N/A | N/A |
| date | 1,000,000 | 100 | 365 | 20160101 | 20161231 | 20160816 |
| ssn | 1,000,000 | 100 | 835819 | N/A | N/A | 999999999 |
| firstname | 1,000,000 | 100 | 78136 | N/A | N/A | EAMSTRMT |
| lastname | 1,000,000 | 100 | 177001 | N/A | N/A | ERJSAXA |
| address | 1,000,000 | 100 | 828774 | N/A | N/A | 123 MAIN ST |
| zip5 | 1,000,000 | 100 | 26370 | N/A | N/A | 68138 |
| dob | 1,000,000 | 100 | 42673 | 19000101 | 20161031 | 19070626 |
| homephone | 1,000,000 | 100 | 28244 | N/A | N/A | 9999999999 |
| fraud_label | 1,000,000 | 100 | 2 | N/A | N/A | 0 |

**Table 1.1: Summary Table For All Fields in Dataset**

For each field, we plotted the distribution and the most frequent occurrences to better understand the nature of our data before creating any candidate variables. Our plots were organized into a data quality report, which can be found in the appendix. The following distributions and bar charts highlight some important characteristics of our dataset.

Date

The volume of applications were fairly similar throughout the year with hikes around the beginning of each new quarter.

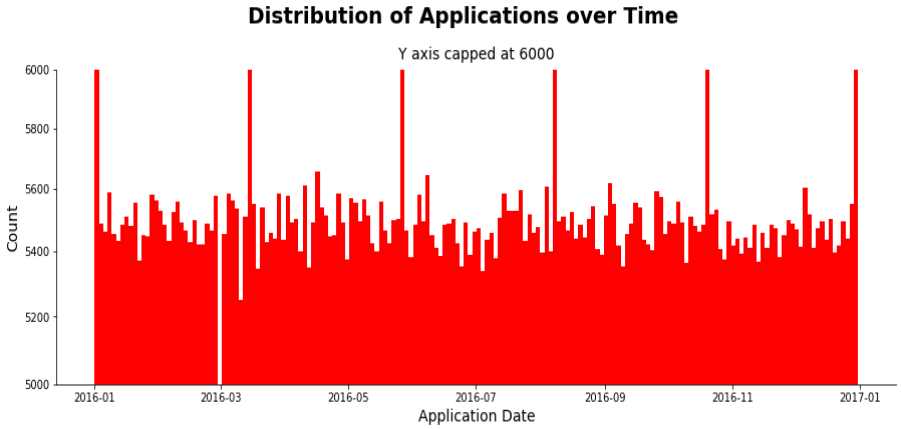



**Figure 1.1: Distribution of Application Dates Over Time**

SSN

Social security number ‘999999999’ was most frequently used and led us to conclude that it is likely a frivolous value, a value that was originally missing, but filled with a new common value.

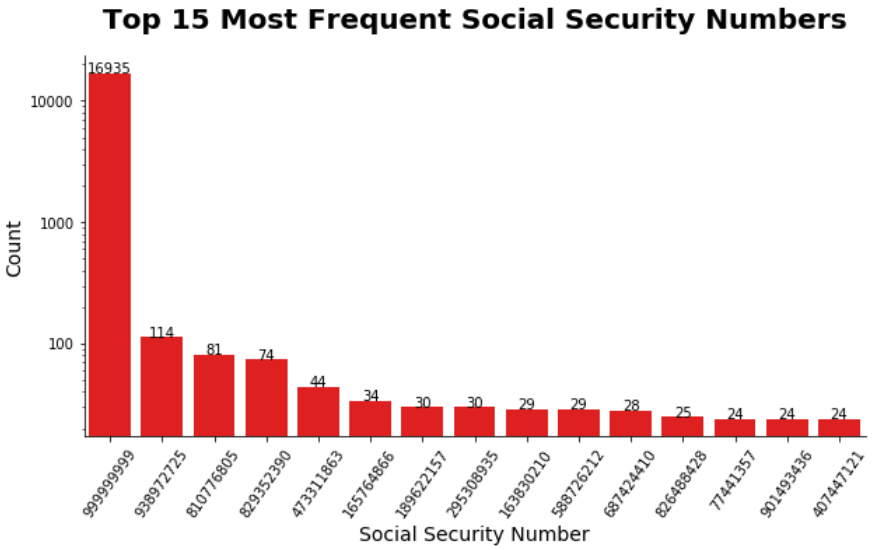



**Figure 1.2: Most Frequent Social Security Numbers**

Address

‘123 Main Street’ appeared significantly more than the other addresses and led us to believe that it was also a frivolous value.

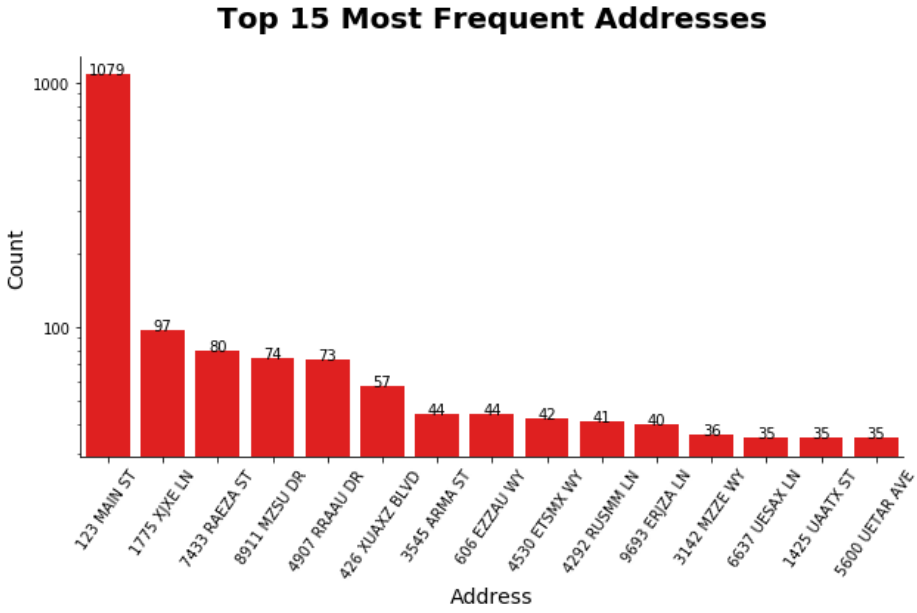



**Figure 1.3 Most Frequent Applicant Address**

Zip Code

Postal code ‘68138’ was most frequently used, but the total count was not much larger than other postal codes so we decided to not classify it as a frivolous value.

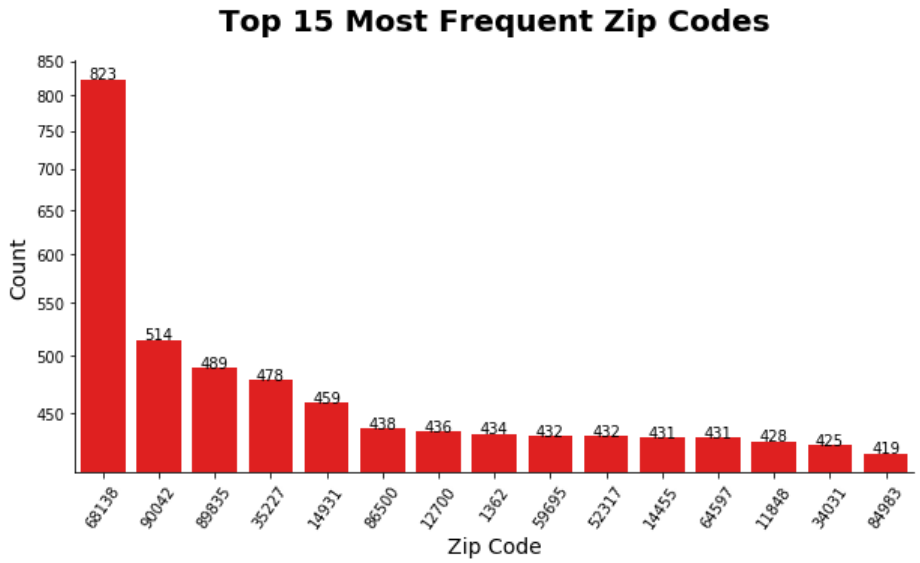



**Figure 1.4 Most Frequent Zip Codes**

Homephone

Home phone number ‘999999999’ was by far the most frequently used, indicating that it is likely a frivolous value.

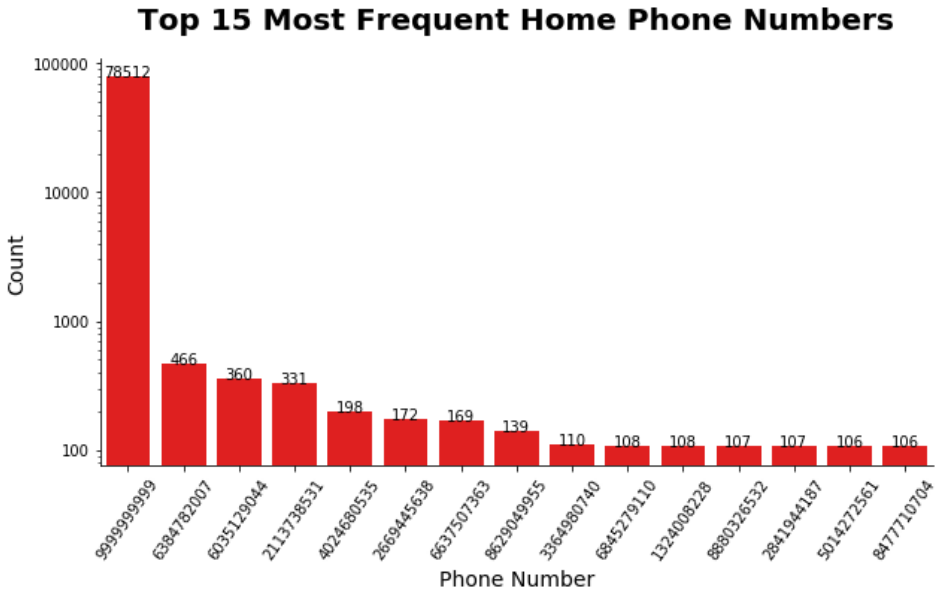



**Figure 1.5 Most Frequent Phone Numbers**

## Data Cleaning

After initial investigation into the dataset, we discovered that all fields were 100% populated, therefore we did not need to treat any missing values. However, we discovered that there were frivolous values in four of the fields, shown in Table 2.1.

| Field | Frivolous Value | Count |
|---|---|---|
| ssn | 9999999999 | 16,935 |
| address | 123 MAIN ST | 1,079 |
| dob | 19070626 | 126,568 |
| homephone | 9999999999 | 78,512 |

**Table 2.1:** Count of Frivolous Values

Frivolous values are made-up values that are used to fill in missing values in a credit application. These values are risky as they could accidentally link two completely unrelated applications. Hence, before proceeding with any further actions on our dataset, frivolous values must be cleaned and replaced in order to avoid undesired results and false conclusions.

There are different approaches to treat frivolous values. For this project, we decided to replace these values with a unique value that will not link.

We chose to replace each frivolous value in field *ssn*, *dob* and *homephone* with the negative of its corresponding unique record number and added leading zeros. For instance, if record # 100 has a value of “9999999999” in the *ssn* field, a value of “19070626” in the *dob* field and a value of “9999999999” in the *homephone* field, these frivolous values were replaced with “-000000100”.

For each frivolous value in the *address* field, we chose to replace it with its corresponding unique record number, and append the string “ RECORD” to the end. For instance, if record # 101 has a value of “123 MAIN ST” in the *address* field, the frivolous value was replaced with “101 RECORD”.

To maintain data type consistency, all four aforementioned data fields were converted into string types after treating the frivolous values. The *date* and *zip5* fields were also converted into datetime and string type respectively.

## Candidate Variables

After handling frivolous values, we built 393 new variables from the original identity fields from four different categories.

Apart from the original identity fields, we derived four new fields, which were used when creating variables. We first created an Age variable which is the date difference between the date of birth and application date. Then, we created age bins with eight buckets with boundaries of [<13.75, <28.5, <43.25, <58, <72.75, <87.5, <102.25, <117]. An area code was extracted from the first three digits of the home phone number. Lastly, we found the dow, which is an abbreviation of day of week, for the weekday an application was submitted.

Next, we created two new identity fields: *namedob* and *fulladdress*. *Namedob* was created by appending applicant's first name and last name, followed by their date of birth. Full address was made by appending address and zip code.

We created unique attributes using unique combinations of two or more identity fields and linking entities. The entities used for linking were *ssn*, *fulladdress*, *namedob*, and *homephone*. A total of 26 new attributes were created from this process. One attribute example is *ssn_name_dob* where applicant's ssn, name, and date of birth are concatenated.

The final step was to create numerical variables. The first variable created was dow_risk, which uses targeted encoding to assign each weekday the fraud proportion on that specific day of the week. To avoid overfitting, we used a smoothing formula with c=4 and nmid=20. Another similar variable we created was the *Age_bin_risk,* which encoded our age bins with the fraud proportion for each age group. We chose the smoothing parameter c=4 and nmid=20 for *age_bin_risk*.

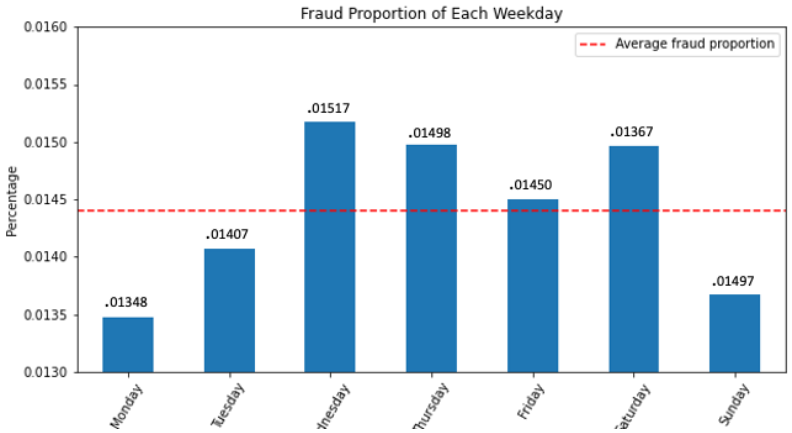



**Figure 3.1 Day of Week Risk Table**

Our next set of variables focused on using time windows to capture the fraudulent application activity over a period of time. The *{attribute}_days_since* variables show how many days have passed since that attribute was last observed. In case that attribute was not seen before, or in other words, this is the first time this attribute has appeared, the value was filled with 365. One example of this variable is *name_dob_days_since*, which is the number of days since that same *namedob* was observed. A total of 26 days since variables were created.

The next variable type looked at the velocity, *{attribute}_count_{n},* which captures the number of times that the same attribute has appeared in the past n days. For n, we chose 6 different time windows: 0, 1, 3, 7, 14, 30 days. As an example, *name_dob_count_7* represents the number of times that the identity with the same name and date of birth was seen in the last 7 days. We created 156 total variables of the velocity type, which were all the combinations of our 26 attributes and 6 time windows.

$$\frac{\#\text{ apps with that } \textbf{\textit{group}} \text{ seen in the recent past}}{\#\text{ apps with that } \textbf{\textit{same group}} \text{ seen in the past } (1, 3, 7, 14, 30) \text{ days}}$$

**Figure 3.2 Relative Velocity Formula**

The last type is the relative velocity, *{attribute}_count_{n_recent}_{n_past}*, which captures the ratio of the amount of times an attribute was seen in the last 0 and 1 days (n_recent) to the amount of times that same attributes was seen in past 3, 7, 14, 30 days (n_past). In other words, it finds the relative recent activity of an attribute compared to longer past periods. For instance, *name_dob_count_0_by_7* is the proportion that an attribute with the same name and date of birth was seen in the past 0 day over the last 7 days. Using the combinations of the 26 attributes, two n_recent days, and four n_past days, we created 208 (26*2*4) variables of this type.

A full list of all the created candidate variables can be found in the appendix.

## Feature Selection Process

After creating 393 candidate variables, it became necessary to reduce dimensionality and find the most informative, substantial variables for our prediction purposes. By reducing the number of features, our model would have fewer chances of fitting data noise and thus improve overall prediction accuracy. In this feature selection process, we implemented a 2-step method to obtain a final list of 30 expert variables to use for our model building.

### Filter Method

Our first step for feature selection was to apply a filter on our 393 variables to reduce to a ranked list of the top 80. Our filter method ranked all variables in order of how individually important each was to predicting the fraud label. The filter method is fast and stable, which enables us to quickly sort and rank the potentially useful candidate variables without running any time-consuming algorithms.

We calculated two metrics, Kolmogorov-Smirnov (KS) statistic and Fraud Detection Rate (FDR) when only using 3% of data, and created a synthetic score by averaging their ranks in order of importance. The KS score is a measure of how separated two classes are given one candidate variable. Therefore, a variable is considered more important to our prediction target if it has a higher KS statistic, as it can help us better distinguish data points between two classes (fraud and non-fraud). The FDR at 3%, on the other hand, measures the percentage of all fraud found for a single, sorted candidate variable. Fraud is by nature extremely hard to detect and also an event that happens relatively rarely in the real-life situation, so a strong candidate variable has to perform well even if only a small amount of data is given. Therefore, we calculated KS and FDR and averaged them to get a balanced measure of importance.

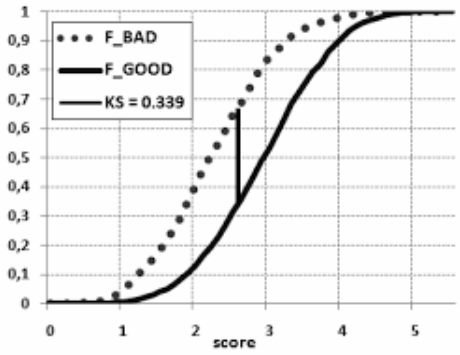



**Figure 4.1: KS Statistic Explanation** - A measure of how separated two classes are given each candidate variable

To make sure our scoring was reliable, we added two special variables to the list of candidate variables: a copy of the fraud label and a randomly generated variable. As we saw in the output,

the fraud label copy was ranked as 1 out of all 395 (393 candidates plus two) variables, and the random variable ranked near the bottom. This indicated we had precise calculations and ensured the reliability of the sorted list.

| Candidate Variables | Scores | |
|---|---|---|
| | ks | fdr |
| fraud_label | 1 | 1 |
| age | 0.0757792 | 0.0426606 |
| dow_risk | 0.0220876 | 0.0392652 |
| age_bin_risk | 0.0712698 | 0.0418771 |
| ssn_day_since | 0.227255 | 0.260839 |
| ... | ... | ... |
| ssn_homephone_name_dob_count_1_by_3 | 0.0096551 | 0.0491033 |
| ssn_homephone_name_dob_count_1_by_7 | 0.0254564 | 0.0646004 |
| ssn_homephone_name_dob_count_1_by_14 | 0.0446558 | 0.0812293 |
| ssn_homephone_name_dob_count_1_by_30 | 0.0600989 | 0.0939404 |
| random | 0.00955982 | 0.0363921 |

**Table 4.1: Unsorted Calculation of KS and FDR Score for All Candidate Variables**

| Candidate Variables | Scores | | Ranks | | |
|---|---|---|---|---|---|
| | ks | fdr | rank_ks | rank_fdr | average_rank |
| fraud_label | 1 | 1 | 395 | 395 | 395 |
| address_day_since | 0.334096 | 0.366794 | 394 | 394 | 394 |
| fulladdress_day_since | 0.33321 | 0.364531 | 393 | 393 | 393 |
| fulladdress_count_30 | 0.332032 | 0.36427 | 391 | 392 | 391.5 |
| address_count_30 | 0.332725 | 0.363399 | 392 | 391 | 391.5 |
| ... | ... | ... | ... | ... | ... |
| fulladdress_dob_count_0 | 0.001812 | 0.044315 | 8 | 8 | 8 |
| ssn_fulladdress_count_0 | 0.001774 | 0.044315 | 5.5 | 8 | 6.75 |
| ssn_name_fulladdress_count_0 | 0.001774 | 0.044315 | 5.5 | 8 | 6.75 |
| ssn_fulladdress_dob_count_0 | 0.001729 | 0.044315 | 3 | 8 | 5.5 |
| ssn_name_homephone_count_0 | 0.001708 | 0.044228 | 1 | 5 | 3 |

**Table 4.2: Sorted Rank of Candidate Variables Based on Average Score of KS and FDR**

## Wrapper Method

After finding the top 80 candidate variables from the KS-FDR filter, we further reduced the number of candidate variables to 30 by applying a wrapper method. A wrapper method, specifically a backward selection method, builds a single classification model using all variables and removes one variable at a time, starting with the least important variable on the list. We decided to use logistic regression as the underlying model due to its effectiveness and simpleness.

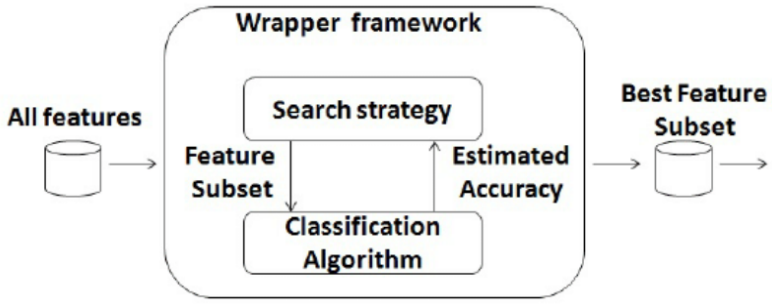



**Figure 4.2: Wrapper Method Explanation** - This method uses an algorithm to select the best candidate variables

We first applied this wrapper method with the built-in function from the sklearn.feature_selection package that returned the best number of features based on recursive feature elimination and cross-validated selection.

However, our initial list ranked many variables as 1, which indicated our method couldn't distinguish the importance of candidate variables. We came up with two strategies for making changes to the wrapper. The first alternative was to use an advanced non-linear model like a decision tree, as they might capture non-linear patterns in our dataset compared to logistic regression. The second alternative was to skip cross-validation in the wrapper process, as the cross-validation would improve model performance as much as possible, thus the algorithm couldn't effectively rank candidates. We implemented the second alternative and created a well-ranked list of 30 variables that could best contribute to the prediction of fraud probability.

| Final Variables | | | |
|---|---|---|---|
| | **ranking** | **variable** | **Description** |
| 0 | 1 | address_count_0 | Number of times that the same address has occurred in the same day |
| 1 | 1 | address_count_0_by_7 | The ratio that the same address was seen in the last 0 day to it seen in the past 7 days |
| 2 | 1 | address_count_1_by_7 | The ratio that the same address was seen in the last 1 day to it seen in the past 7 days |
| 3 | 1 | address_count_7 | Number of times that the same address has occurred in the past 7 days |
| 4 | 1 | fulladdress_count_0_by_7 | The ratio that 'fulladdress_homephone' was seen in the last 1 day to it seen in the past 7 days |
| 5 | 1 | fulladdress_homephone_count_3 | Number of times that the same fulladdress_homephone has occurred in the past 3 days |
| 6 | 1 | fulladdress_homephone_count_7 | Number of times that the same fulladdress_homephone has occurred in the past 7 days |
| 7 | 1 | homephone_count_1 | Number of times that the same homephone has occurred in the past 1 days |
| 8 | 1 | name_dob_count_14 | Number of times that the same name_dob has occurred in the past 14 days |
| 9 | 1 | name_dob_count_30 | Number of times that the same name_dob has occurred in the past 30 days |
| 10 | 1 | ssn_count_14 | Number of times that the same ssn has occurred in the past 14 days |
| 11 | 1 | ssn_dob_count_14 | Number of times that the same ssn_dob has occurred in the past 14 days |
| 12 | 1 | ssn_firstname_count_7 | Number of times that the same ssn_firstname has occurred in the past 7 days |
| 13 | 2 | fulladdress_count_0 | Number of times that the same fulladdress has occurred in the same day |
| 14 | 4 | fulladdress_count_30 | Number of times that the same fulladdress has occurred in the past 30 days |
| 15 | 10 | fulladdress_count_1 | Number of times that the same fulladdress has occurred in the past 1 day |
| 16 | 12 | fulladdress_count_0_by_14 | The ratio that the same fulladdress was seen in the last 0 day to it seen in the past 14 days |
| 17 | 13 | ssn_count_3 | Number of times that the same ssn has occurred in the past 3 days |
| 18 | 14 | fulladdress_count_0_by_3 | The ratio that the same fulladdress was seen in the last 0 day to it seen in the past 3 days |
| 19 | 17 | ssn_dob_count_3 | Number of times that the same ssn_dob has occurred in the past 3 days |
| 20 | 20 | ssn_count_7 | Number of times that the same ssn has occurred in the past 7 days |
| 21 | 21 | ssn_dob_count_0_by_14 | The ratio that the same ssn_dob was seen in the last 0 day to it seen in the past 14 days |
| 22 | 23 | ssn_firstname_count_3 | Number of times that the same ssn_firstname has occurred in the past 3 days |
| 23 | 26 | address_count_0_by_3 | The ratio that the same address was seen in the last 0 day to it seen in the past 3 days |
| 24 | 27 | name_dob_count_3 | Number of times that the same name_dob has occurred in the past 3 days |
| 25 | 28 | address_count_1 | Number of times that the same address has occurred in the past 1 day |
| 26 | 29 | ssn_firstname_count_30 | Number of times that the same ssn_firstname has occurred in the past 30 days |
| 27 | 31 | ssn_count_30 | Number of times that the same ssn has occurred in the past 30 days |
| 28 | 33 | ssn_firstname_count_14 | Number of times that the same ssn_firstname has occurred in the past 14 days |
| 29 | 34 | ssn_dob_count_30 | Number of times that the same dob has occurred in the past 30 days |

**Table 4.3: A Final List of 30 Candidate Variables Selected**

Based on the output of the wrapper method

# Model Algorithms

As we are attempting to identify applications as potential fraud, the most appropriate modeling approach was to build a binary classification model. Before training our models, we split our data into two sets: a train and test set made up of applications prior to October 31st, 2016 and an out-of-time (OOT) set made of applications that we received after October 31st, 2016. Our train and test data were split into a 75% training group and a 25% testing group.

Since roughly 1.5% of our fields were flagged as frauds, we had a potential imbalanced data issue. As a remedy, we utilized three different sampling techniques: undersampling, SMOTE, and tuning the weight parameter within the algorithm. Undersampling is a technique where you down sample the majority class to meet a specific ratio with the minority class. Synthetic minority oversampling technique (SMOTE) can be used to synthetically generate more minority classes, by taking the nearest neighbors of all "bad" records and creating similar ones. Lastly, some algorithms have a weight parameter to inform the model of different class weights. We used a ratio of 10 "goods" to 1 "bad" as our parameter setting for some models to place more emphasis on the "bad" records by minimizing the ratio between the two classes.

We tested four different algorithms across many different hyperparameters to determine which method would be the most effective in finding identity fraud.

### Logistic Regression

Our first algorithm used logistic regression, a linear classifier algorithm. This algorithm outputs a probability of a record being identified as fraud by using the logistic sigmoid function which forms a sideways S curve on a graph. In order to map these probabilities to a prediction, we use a linear decision boundary to assign records to specific classes. The hyperparameters we controlled for in our model were the penalty parameter which controls regularization, C another regularization term, and the solver which is used for optimizing the algorithm.

| Model | Parameters | | | | | Average FDR at 3% | | |
|---|---|---|---|---|---|---|---|---|
| | Iteration | Sampling Strategy (Majority:Minority) | penalty | C | solver | Train | Test | OOT |
| Logistic Regression | 1 | No Sampling | l2 | 1 | liblinear | 52.51 | 52.14 | 50.00 |
| | 2 | Class weight Argument (10:1) | l2 | 1 | liblinear | 52.81 | 52.48 | 50.84 |
| | 3 | SMOTE (70:30) | l2 | 1 | liblinear | 53.50 | 53.15 | 51.30 |
| | 4 | SMOTE (60:40) | l2 | 1 | liblinear | 53.94 | 53.41 | 51.30 |
| | 5 | SMOTE (50:50) | l2 | 1 | liblinear | 53.95 | 53.41 | 51.30 |
| | 6 | Undersample (70:30) | l2 | 1 | liblinear | 54.43 | 53.92 | 52.14 |
| | 7 | Undersample (60:40) | l2 | 1 | liblinear | 54.20 | 53.88 | 52.14 |
| | 8 | Undersample (50:50) | l2 | 1 | liblinear | 54.53 | 53.85 | 52.10 |
| | 9 | No Sampling | l2 | 0.1 | saga | 54.55 | 53.82 | 51.72 |
| | 10 | Undersample (70:30) | l2 | 0.1 | saga | 54.65 | 53.92 | 52.10 |
| | 11 | SMOTE (70:30) | l2 | 0.1 | saga | 54.14 | 53.55 | 51.26 |
| | 12 | No Sampling | l2 | 0.01 | lbfgs | 53.33 | 52.54 | 50.80 |
| | 13 | Undersample (70:30) | l2 | 0.01 | lbfgs | 53.89 | 53.18 | 51.34 |

**Table 5.1 Logistic Regression Hyperparameter Performance Table**

## Random Forest

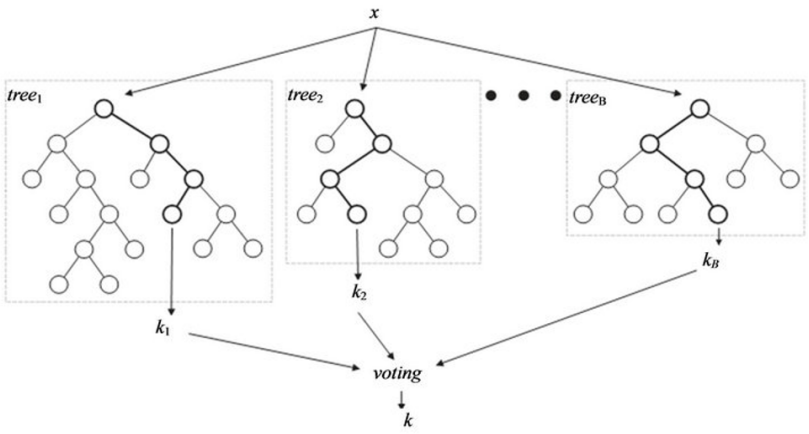



**Figure 5.1: Random Forest Explanation:** A collection of many strong models with averaged scoring

The next modeling algorithm we tried was a Random Forest, an ensemble method that averages many strong decision tree models to build a more accurate and stable prediction. On a high level, a decision tree works by carving up spaces into boxes and assigns a model output for each carved box. Random Forest builds a collection of many of these decision tree models, selecting a random subset of variables or records, and votes based on the outputs of each model to flag a record as fraud or not. We tried a wide range of hyperparameters, including the number of trees, the depth of each tree, the criterion to measure the quality of each split, and the minimum number of samples required to split an internal node.

| Model | Parameters | | | | | | Average FDR at 3% | | |
|---|---|---|---|---|---|---|---|---|---|
| | Iteration | Sampling Strategy (Majority:Minority) | criterion | n_estimators | max_depth | min_samples_split | Train | Test | OOT |
| Random Forest | 1 | No Sampling | gini | 100 | 20 | 300 | 55.59 | 55.06 | 53.35 |
| | 2 | Class Weight Argument (10:1) | gini | 100 | 20 | 300 | 55.66 | 55.09 | 53.56 |
| | 3 | SMOTE (70:30) | gini | 100 | 20 | 300 | 55.75 | 55.09 | 51.55 |
| | 4 | Undersample (70:30) | gini | 100 | 20 | 300 | 55.38 | 54.60 | 52.98 |
| | 5 | Class Weight Argument (10:1) | entopry | 150 | 10 | 200 | 55.51 | 54.76 | 53.35 |
| | 6 | Class Weight Argument (10:1) | entopry | 150 | 25 | 300 | 55.73 | 55.06 | 53.48 |
| | 7 | Class Weight Argument (10:1) | entopry | 150 | 30 | 400 | 55.67 | 55.12 | 53.52 |
| | 8 | Class Weight Argument (10:1) | gini | 100 | 20 | 400 | 55.71 | 55.12 | 53.52 |
| | 9 | Class Weight Argument (10:1) | gini | 50 | 25 | 300 | 55.65 | 55.06 | 53.44 |
| | 10 | Class Weight Argument (10:1) | gini | 50 | 25 | 300 | 55.69 | 54.99 | 53.56 |

**Table 5.2 Random Forest Hyperparameter Performance Table**

## XGBoost

Another modeling algorithm we tested was XGBoost, a gradient boosting algorithm. XGBoost iteratively trains a series of weak models, correcting the previous errors to result in stronger predictions. These additional models will continue to be added sequentially until no further improvements can be made. It uses a gradient descent algorithm as a way of minimizing the errors for each new tree that is added to the model. We focused on tunning the number of trees, the learning rate for preventing overfitting, the max depth of each tree, and the ratio for sampling the training data prior to building any trees.

| Model | Parameters | | | | | | Average FDR at 3% | | |
|---|---|---|---|---|---|---|---|---|---|
| | Iteration | Sampling Strategy (Majority:Minority) | learning_rate | n_estimators | max_depth | subsample | Train | Test | OOT |
| XGBoost | 1 | No Sampling | 0.1 | 400 | 3 | 1 | 57.61 | 55.22 | 53.31 |
| | 2 | Scale Pos Weight = 10 | 0.1 | 400 | 3 | 1 | 62.56 | 55.02 | 53.02 |
| | 3 | SMOTE (70:30) | 0.1 | 400 | 3 | 1 | 58.28 | 54.89 | 49.75 |
| | 4 | Undersample (70:30) | 0.1 | 400 | 3 | 1 | 57.33 | 54.89 | 52.85 |
| | 5 | No Sampling | 0.05 | 500 | 5 | 0.7 | 56.92 | 55.35 | 53.10 |
| | 6 | No Sampling | 0.1 | 750 | 5 | 0.8 | 59.49 | 55.02 | 52.68 |
| | 7 | No Sampling | 0.1 | 750 | 5 | 1 | 58.54 | 54.92 | 53.10 |
| | 8 | No Sampling | 0.01 | 1000 | 3 | 1 | 55.65 | 55.29 | 53.25 |
| | 9 | No Sampling | 0.1 | 600 | 3 | 0.8 | 57.04 | 55.46 | 53.19 |
| | 10 | No Sampling | 0.05 | 600 | 5 | 1 | 57.11 | 55.05 | 53.44 |

**Table 5.3 XGBoost Hyperparameter Performance Table**

## Neural Networks

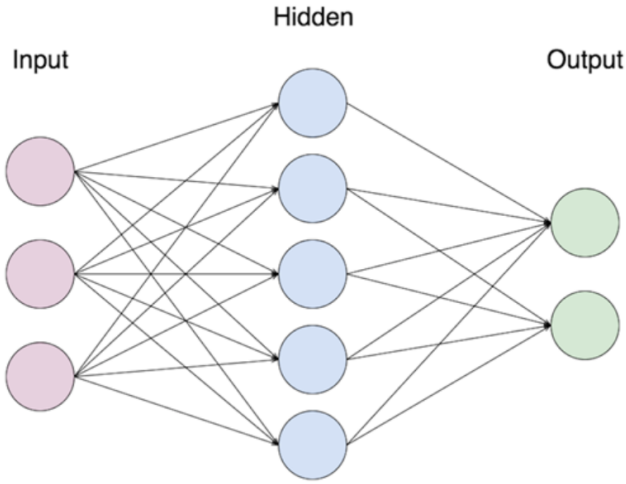



**Figure 5.2 Simple Neural Network with One Hidden Layer and 5 Nodes**

Our last modeling algorithm was a neural network, a method that attempts to mimic human brain activity by using a set of hidden layers and nodes. Each node receives a weighted signal from all the previous layer's nodes and performs a transformation on the linear combinations of all these signals. The data is passed through this model many times, called epochs, and each epoch attempts to reduce the error of the previous run. During each epoch, the weights of the signals are adjusted from each data record, until the weights are tuned to the local optimal point. The hyperparameters that we set were the number of epochs, the number of nodes, and the optimization function.

| Model | Parameters | | | | | | | Average FDR at 3% | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Iteration | Sampling Strategy (Majority:Minority) | optimizer | layers | nodes | epochs | activation | Train | Test | OOT |
| Neural Networks | 1 | No Sampling | adam | 1 | 20 | 10 | relu | 55.22 | 54.46 | 52.18 |
| | 2 | SMOTE (70:30) | adam | 1 | 20 | 10 | relu | 55.60 | 54.73 | 52.56 |
| | 3 | Undersample (70:30) | adam | 1 | 20 | 10 | relu | 54.44 | 54.14 | 52.01 |
| | 4 | SMOTE (70:30) | sgd | 1 | 10 | 20 | relu | 54.47 | 54.01 | 52.05 |
| | 5 | SMOTE (70:30) | sgd | 1 | 30 | 20 | relu | 55.25 | 54.53 | 52.31 |
| | 6 | SMOTE (70:30) | sgd | 1 | 30 | 30 | relu | 55.25 | 54.53 | 52.26 |
| | 7 | SMOTE (70:30) | adam | 1 | 50 | 30 | relu | 55.59 | 54.73 | 53.19 |
| | 8 | SMOTE (70:30) | adam | 1 | 30 | 40 | relu | 55.59 | 55.09 | 52.72 |
| | 9 | SMOTE (70:30) | adam | 1 | 50 | 40 | relu | 55.72 | 55.12 | 53.02 |
| | 10 | SMOTE (70:30) | adam | 1 | 50 | 20 | relu | 55.61 | 54.76 | 53.23 |

**Table 5.4 Neural Network Hyperparameter Performance Table**

# Results

After creating 43 models across four different base algorithms, we discovered that our best performing model was an XGBoost algorithm with a 55.46% fraud detection rate at 3% for the test data set. The hyperparameters were set to:

- 600 Estimators
- Max depth of 3
- Learning rate of 0.1
- Random Subsample ratio at 0.8

The full model performance table can be found in the appendix.

| Model | Parameters | | | | | | | Average FDR at 3% | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Logistic Regression | Iteration | Sampling Strategy (Majority:Minority) | penalty | C | solver | | | Train | Test | OOT |
| | 1 | No Sampling | l2 | 1 | liblinear | | | 52.51 | 52.14 | 50.00 |
| XGBoost | Iteration | Sampling Strategy (Majority:Minority) | learning_rate | n_estimators | max_depth | subsample | | Train | Test | OOT |
| | 1 | No Sampling | 0.1 | 400 | 3 | 1 | | 55.37 | 56.26 | 53.56 |
| Random Forest | Iteration | Sampling Strategy (Majority:Minority) | criterion | n_estimators | max_depth | min_samples_split | | Train | Test | OOT |
| | 1 | No Sampling | gini | 100 | 20 | 300 | | 55.59 | 55.06 | 53.35 |
| Neural Networks | Iteration | Sampling Strategy (Majority:Minority) | optimizer | layers | nodes | epochs | activation | Train | Test | OOT |
| | 1 | No Sampling | adam | 1 | 20 | 10 | relu | 55.22 | 54.46 | 52.18 |

**Table 6.1 Performance Table of the Four Best Models:** One iteration selected from each model

In the training set the top population bin was comprised of over 75.6% fraudulent records, with similar results across test, and out of time. This model helps ensure that investigators have to sift through minimal numbers of false positives.

| Training | # Records | # Goods | # Bads | Fraud Rate |
|---|---|---|---|---|
| | 625130 | 616125 | 9005 | 0.01440500376 |

| | Bin Statistics | | | | | Cumulative Statistics | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Population Bin % | # Records | # Goods | # Bads | % Goods | % Bads | Total # Records | Cumulative Goods | Cumulative Bads | % Goods | % Bads (FDR) | KS | FPR |
| 1 | 6250 | 1525 | 4725 | 24.40% | 75.60% | 6250 | 1525 | 4725 | 0.25% | 52.47% | 52.22 | 0.32 |
| 2 | 6251 | 6070 | 181 | 97.10% | 2.90% | 12501 | 7595 | 4906 | 1.23% | 54.48% | 53.25 | 1.55 |
| 3 | 6251 | 6171 | 80 | 98.72% | 1.28% | 18752 | 13766 | 4986 | 2.23% | 55.37% | 53.13 | 2.76 |
| 4 | 6252 | 6205 | 47 | 99.25% | 0.75% | 25004 | 19971 | 5033 | 3.24% | 55.89% | 52.65 | 3.97 |
| 5 | 6251 | 6195 | 56 | 99.10% | 0.90% | 31255 | 26166 | 5089 | 4.25% | 56.51% | 52.27 | 5.14 |
| 6 | 6251 | 6198 | 53 | 99.15% | 0.85% | 37506 | 32364 | 5142 | 5.25% | 57.10% | 51.85 | 6.29 |
| 7 | 6252 | 6213 | 39 | 99.38% | 0.62% | 43758 | 38577 | 5181 | 6.26% | 57.53% | 51.27 | 7.45 |
| 8 | 6251 | 6212 | 39 | 99.38% | 0.62% | 50009 | 44789 | 5220 | 7.27% | 57.97% | 50.70 | 8.58 |
| 9 | 6251 | 6213 | 38 | 99.39% | 0.61% | 56260 | 51002 | 5258 | 8.28% | 58.39% | 50.11 | 9.70 |
| 10 | 6251 | 6198 | 53 | 99.15% | 0.85% | 62511 | 57200 | 5311 | 9.28% | 58.98% | 49.69 | 10.77 |
| 11 | 6252 | 6207 | 45 | 99.28% | 0.72% | 68763 | 63407 | 5356 | 10.29% | 59.48% | 49.19 | 11.84 |
| 12 | 6251 | 6212 | 39 | 99.38% | 0.62% | 75014 | 69619 | 5395 | 11.30% | 59.91% | 48.61 | 12.90 |
| 13 | 6251 | 6196 | 55 | 99.12% | 0.88% | 81265 | 75815 | 5450 | 12.31% | 60.52% | 48.22 | 13.91 |
| 14 | 6252 | 6197 | 55 | 99.12% | 0.88% | 87517 | 82012 | 5505 | 13.31% | 61.13% | 47.82 | 14.90 |
| 15 | 6251 | 6201 | 50 | 99.20% | 0.80% | 93768 | 88213 | 5555 | 14.32% | 61.69% | 47.37 | 15.88 |
| 16 | 6251 | 6205 | 46 | 99.26% | 0.74% | 100019 | 94418 | 5601 | 15.32% | 62.20% | 46.87 | 16.86 |
| 17 | 6252 | 6209 | 43 | 99.31% | 0.69% | 106271 | 100627 | 5644 | 16.33% | 62.68% | 46.34 | 17.83 |
| 18 | 6251 | 6214 | 37 | 99.41% | 0.59% | 112522 | 106841 | 5681 | 17.34% | 63.09% | 45.75 | 18.81 |
| 19 | 6251 | 6205 | 46 | 99.26% | 0.74% | 118773 | 113046 | 5727 | 18.35% | 63.60% | 45.25 | 19.74 |
| 20 | 6251 | 6217 | 34 | 99.46% | 0.54% | 125024 | 119263 | 5761 | 19.36% | 63.98% | 44.62 | 20.70 |

**Table 6.2 Training Results**

Our process was validated by an equally impressive test dataset prediction, with excellent results across FDR, purity, and KS. Of the 208377 records, almost 1700 of the 3000 frauds were caught in the 1% population bin.

| Testing | # Records | # Goods | # Bads | Fraud Rate |
|---|---|---|---|---|
| | 208377 | 205375 | 3002 | 0.01440658038 |

| | Bin Statistics | | | | | Cumulative Statistics | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Population Bin % | # Records | # Goods | # Bads | % Goods | % Bads | Total # Records | Cumulative Goods | Cumulative Bads | % Goods | % Bads (FDR) | KS | FPR |
| 1 | 2082 | 471 | 1611 | 22.62% | 77.38% | 2082 | 471 | 1611 | 0.23% | 53.66% | 53.43 | 0.29 |
| 2 | 2084 | 2034 | 50 | 97.60% | 2.40% | 4166 | 2505 | 1661 | 1.22% | 55.33% | 54.11 | 1.51 |
| 3 | 2084 | 2056 | 28 | 98.66% | 1.34% | 6250 | 4561 | 1689 | 2.22% | 56.26% | 54.04 | 2.70 |
| 4 | 2084 | 2064 | 20 | 99.04% | 0.96% | 8334 | 6625 | 1709 | 3.23% | 56.93% | 53.70 | 3.88 |
| 5 | 2083 | 2068 | 15 | 99.28% | 0.72% | 10417 | 8693 | 1724 | 4.23% | 57.43% | 53.20 | 5.04 |
| 6 | 2084 | 2070 | 14 | 99.33% | 0.67% | 12501 | 10763 | 1738 | 5.24% | 57.89% | 52.65 | 6.19 |
| 7 | 2084 | 2065 | 19 | 99.09% | 0.91% | 14585 | 12828 | 1757 | 6.25% | 58.53% | 52.28 | 7.30 |
| 8 | 2084 | 2069 | 15 | 99.28% | 0.72% | 16669 | 14897 | 1772 | 7.25% | 59.03% | 51.77 | 8.41 |
| 9 | 2083 | 2069 | 14 | 99.33% | 0.67% | 18752 | 16966 | 1786 | 8.26% | 59.49% | 51.23 | 9.50 |
| 10 | 2084 | 2068 | 16 | 99.23% | 0.77% | 20836 | 19034 | 1802 | 9.27% | 60.03% | 50.76 | 10.56 |
| 11 | 2084 | 2069 | 15 | 99.28% | 0.72% | 22920 | 21103 | 1817 | 10.28% | 60.53% | 50.25 | 11.61 |
| 12 | 2084 | 2072 | 12 | 99.42% | 0.58% | 25004 | 23175 | 1829 | 11.28% | 60.93% | 49.64 | 12.67 |
| 13 | 2084 | 2063 | 21 | 98.99% | 1.01% | 27088 | 25238 | 1850 | 12.29% | 61.63% | 49.34 | 13.64 |
| 14 | 2083 | 2067 | 16 | 99.23% | 0.77% | 29171 | 27305 | 1866 | 13.30% | 62.16% | 48.86 | 14.63 |
| 15 | 2084 | 2069 | 15 | 99.28% | 0.72% | 31255 | 29374 | 1881 | 14.30% | 62.66% | 48.36 | 15.62 |
| 16 | 2084 | 2063 | 21 | 98.99% | 1.01% | 33339 | 31437 | 1902 | 15.31% | 63.36% | 48.05 | 16.53 |
| 17 | 2084 | 2071 | 13 | 99.38% | 0.62% | 35423 | 33508 | 1915 | 16.32% | 63.79% | 47.48 | 17.50 |
| 18 | 2083 | 2063 | 20 | 99.04% | 0.96% | 37506 | 35571 | 1935 | 17.32% | 64.46% | 47.14 | 18.38 |
| 19 | 2084 | 2074 | 10 | 99.52% | 0.48% | 39590 | 37645 | 1945 | 18.33% | 64.79% | 46.46 | 19.35 |
| 20 | 2084 | 2069 | 15 | 99.28% | 0.72% | 41674 | 39714 | 1960 | 19.34% | 65.29% | 45.95 | 20.26 |

**Table 6.3 Testing Results**

To ensure our model would perform well on completely unseen data, we withheld the last 2 months of the year completely from model building. Our model still performed excellently on this out-of-time data with over 53.56% FDR at 3%.

| OOT | # Records | # Goods | # Bads | Fraud Rate |
|---|---|---|---|---|
| | 163772 | 161427 | 2345 | 0.01431868696 |

| | Bin Statistics | | | | | Cumulative Statistics | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Population Bin % | # Records | # Goods | # Bads | % Goods | % Bads | Total # Records | Cumulative Goods | Cumulative Bads | % Goods | % Bads (FDR) | KS | FPR |
| 1 | 1636 | 442 | 1194 | 27.02% | 72.98% | 1636 | 442 | 1194 | 0.27% | 50.92% | 50.64 | 0.37 |
| 2 | 1638 | 1603 | 35 | 97.86% | 2.14% | 3274 | 2045 | 1229 | 1.27% | 52.41% | 51.14 | 1.66 |
| 3 | 1638 | 1611 | 27 | 98.35% | 1.65% | 4912 | 3656 | 1256 | 2.26% | 53.56% | 51.30 | 2.91 |
| 4 | 1637 | 1627 | 10 | 99.39% | 0.61% | 6549 | 5283 | 1266 | 3.27% | 53.99% | 50.71 | 4.17 |
| 5 | 1638 | 1629 | 9 | 99.45% | 0.55% | 8187 | 6912 | 1275 | 4.28% | 54.37% | 50.09 | 5.42 |
| 6 | 1638 | 1623 | 15 | 99.08% | 0.92% | 9825 | 8535 | 1290 | 5.29% | 55.01% | 49.72 | 6.62 |
| 7 | 1638 | 1628 | 10 | 99.39% | 0.61% | 11463 | 10163 | 1300 | 6.30% | 55.44% | 49.14 | 7.82 |
| 8 | 1637 | 1621 | 16 | 99.02% | 0.98% | 13100 | 11784 | 1316 | 7.30% | 56.12% | 48.82 | 8.95 |
| 9 | 1638 | 1627 | 11 | 99.33% | 0.67% | 14738 | 13411 | 1327 | 8.31% | 56.59% | 48.28 | 10.11 |
| 10 | 1638 | 1628 | 10 | 99.39% | 0.61% | 16376 | 15039 | 1337 | 9.32% | 57.01% | 47.70 | 11.25 |
| 11 | 1637 | 1623 | 14 | 99.14% | 0.86% | 18013 | 16662 | 1351 | 10.32% | 57.61% | 47.29 | 12.33 |
| 12 | 1638 | 1617 | 21 | 98.72% | 1.28% | 19651 | 18279 | 1372 | 11.32% | 58.51% | 47.18 | 13.32 |
| 13 | 1638 | 1625 | 13 | 99.21% | 0.79% | 21289 | 19904 | 1385 | 12.33% | 59.06% | 46.73 | 14.37 |
| 14 | 1638 | 1621 | 17 | 98.96% | 1.04% | 22927 | 21525 | 1402 | 13.33% | 59.79% | 46.45 | 15.35 |
| 15 | 1637 | 1624 | 13 | 99.21% | 0.79% | 24564 | 23149 | 1415 | 14.34% | 60.34% | 46.00 | 16.36 |
| 16 | 1638 | 1624 | 14 | 99.15% | 0.85% | 26202 | 24773 | 1429 | 15.35% | 60.94% | 45.59 | 17.34 |
| 17 | 1638 | 1623 | 15 | 99.08% | 0.92% | 27840 | 26396 | 1444 | 16.35% | 61.58% | 45.23 | 18.28 |
| 18 | 1637 | 1631 | 6 | 99.63% | 0.37% | 29477 | 28027 | 1450 | 17.36% | 61.83% | 44.47 | 19.33 |
| 19 | 1638 | 1630 | 8 | 99.51% | 0.49% | 31115 | 29657 | 1458 | 18.37% | 62.17% | 43.80 | 20.34 |
| 20 | 1638 | 1628 | 10 | 99.39% | 0.61% | 32753 | 31285 | 1468 | 19.38% | 62.60% | 43.22 | 21.31 |

**Table 6.4 Out of Time Results**

# Conclusions

Our project used a synthetic dataset of one million applications to build a real-time model for finding identity fraud. The original dataset contained various identity fields including social security number, first and last name, address, date of birth, and home phone number. Our first step was to replace frivolous fields, common values used to fill missing fields, with a unique value. Afterwards, we created attributes on different combinations of the identity fields to build over 350 candidate variables focusing on the relative velocity of occurrences and the frequency of specific combinations of the identity fields over time.

After creating our candidate variables, we used a two-step feature selection process to reduce our collection of variables. First, we ran a filter method, selecting variables with the highest average rank of KS and FDR at 3%, to narrow our list of variables to 80. Next, we used a backward feature selection process, with a base logistic regression model, to assign an initial ordering to our most important variables. Lastly, we ran our backward selection process again, without cross validation, to get a well-ranked list of the 30 most important variables.

Using these 30 variables, we created 43 unique models from four different binary classification algorithms: Logistic Regression, Random Forest, XGBoost, and Neural Networks. For each iteration, we tested different sampling strategies and hyperparameters with successful results determined by the highest fraud detection rate on our test dataset. The best performing model used XGBoost, a gradient boosting algorithm, with the hyperparameters tuned to 600 estimators, a max depth of 3, a learning rate of 0.1, and a random subsample ratio of 0.8. This final model produced a fraud detection rate of 53.56% at 3% of the population on the out of time data.

Given more time, we would have liked to create more candidate variables, specifically observing the uniqueness of different attributes and their relationships to application frequency. Another area of interest was to try a different feature selection technique, as RFECV did not work as we originally expected. Lastly, we would have liked to spend more time fine tuning our model's performance by training our model on different subsets containing the misclassified applications. However, our models ability to positively identify 53% of fraud for 3% of the population demonstrates a real business opportunity to utilize our algorithm as an effective way to catch identity fraud in real-time.

# Appendix

## DATA QUALITY REPORT FOR APPLICATIONS DATA

### Description

**Dataset Name**: Product Application Data
**Dataset Purpose**: A synthetic dataset meant to mimic real application data from credit cards and cell phone applications. This dataset was created from analysis of over one billion real US applications over 10 years. The data has similar statistical properties to real data characteristics, such as frequency of similar fields and occurrences of relationships to other fields. The purpose of this dataset is to explore and identify application and identity fraud with only an applicant's identity fields.
**Data Source**: Synthetic Data (ID Analytics)
**Time Period**: 2016-01-01 – 2016-12-31
**Number of Fields**: #10
**Number of Records**: 1,000,000

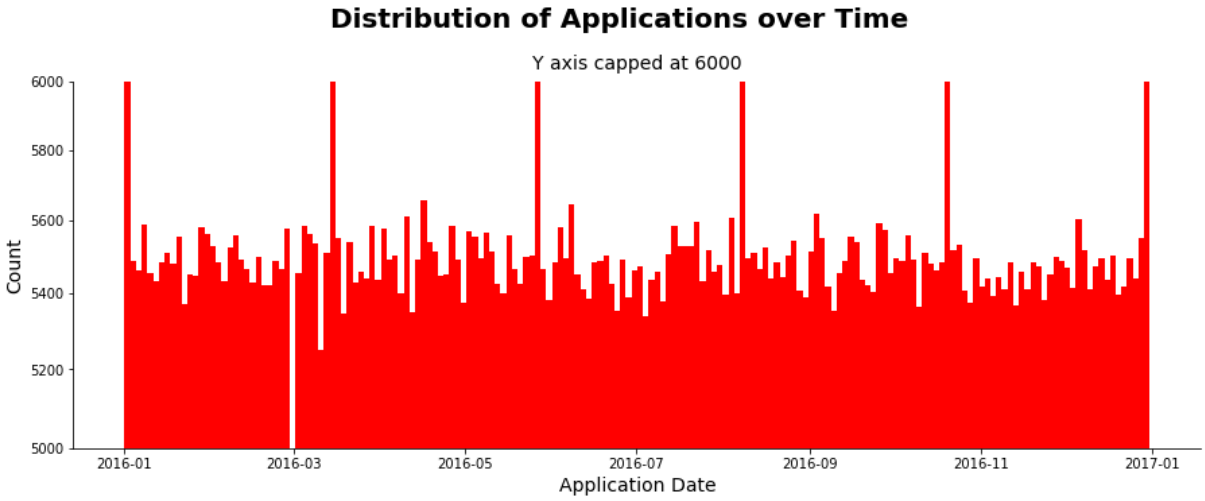
### Summary Table

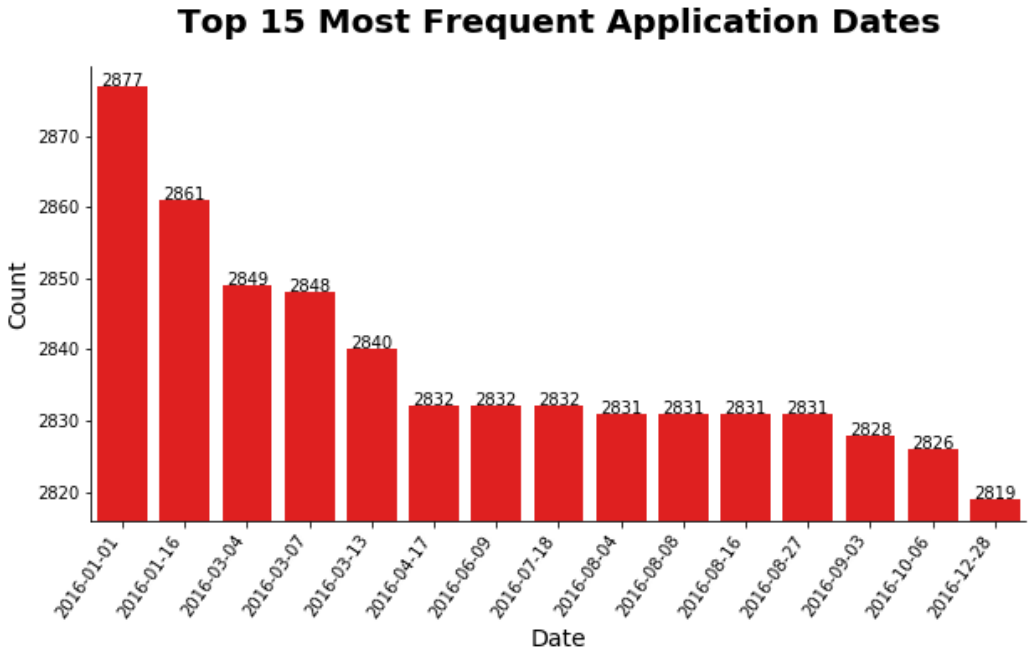
| Column Name | # Records | % Populated | Unique Values | Min | Max | Most Common Field Value |
|---|---|---|---|---|---|---|
| record | 1,000,000 | 100 | 1000000 | N/A | N/A | N/A |
| date | 1,000,000 | 100 | 365 | 20160101 | 20161231 | 20160816 |
| ssn | 1,000,000 | 100 | 835819 | N/A | N/A | 999999999 |
| firstname | 1,000,000 | 100 | 78136 | N/A | N/A | EAMSTRMT |
| lastname | 1,000,000 | 100 | 177001 | N/A | N/A | ERJSAXA |
| address | 1,000,000 | 100 | 828774 | N/A | N/A | 123 MAIN ST |
| zip5 | 1,000,000 | 100 | 26370 | N/A | N/A | 68138 |
| dob | 1,000,000 | 100 | 42673 | 19000101 | 20161031 | 19070626 |
| homephone | 1,000,000 | 100 | 28244 | N/A | N/A | 9999999999 |
| fraud_label | 1,000,000 | 100 | 2 | N/A | N/A | 0 |

### Data Field Exploration:

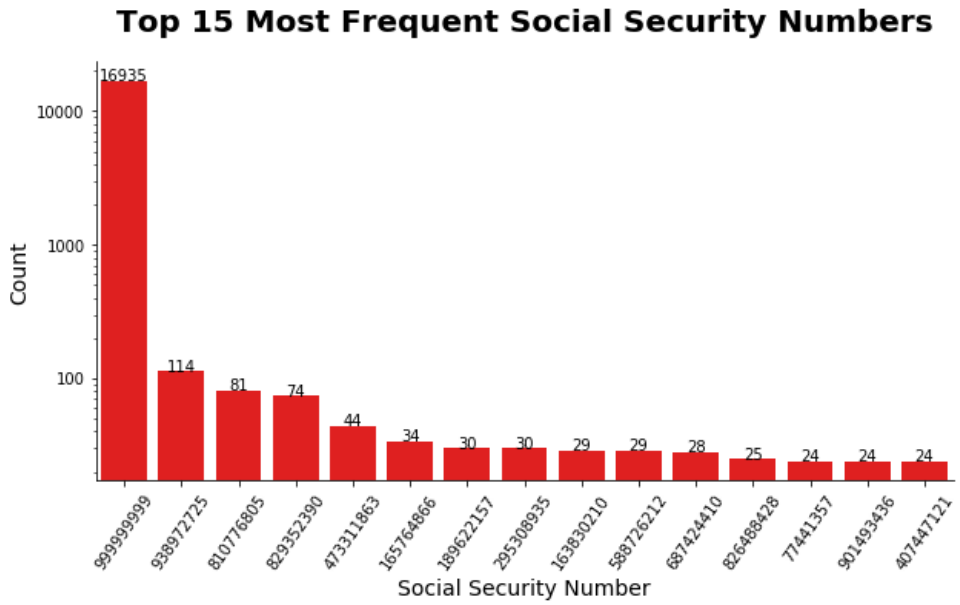
Field 1:
Name: record
Description: Unique identifier of each entry in the data.

Field 2:
Name: date
Description: Date of application

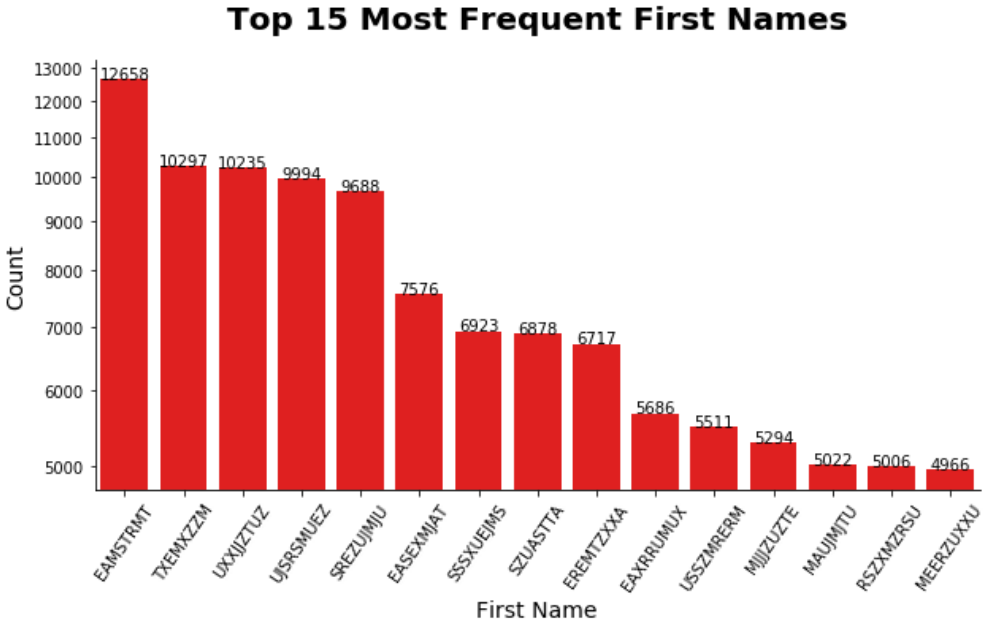


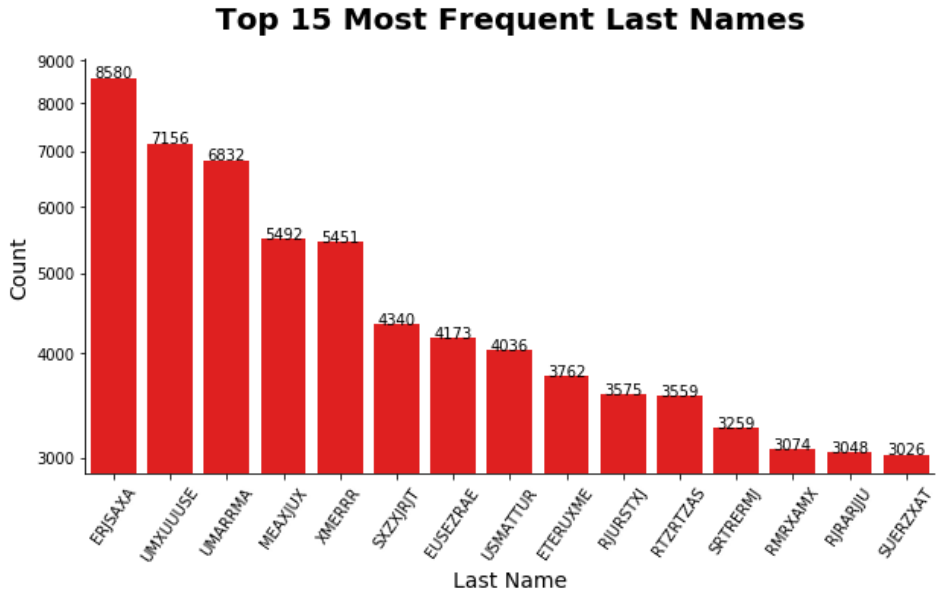
Field 3:
Name: ssn
Description: Social security number of the applicant



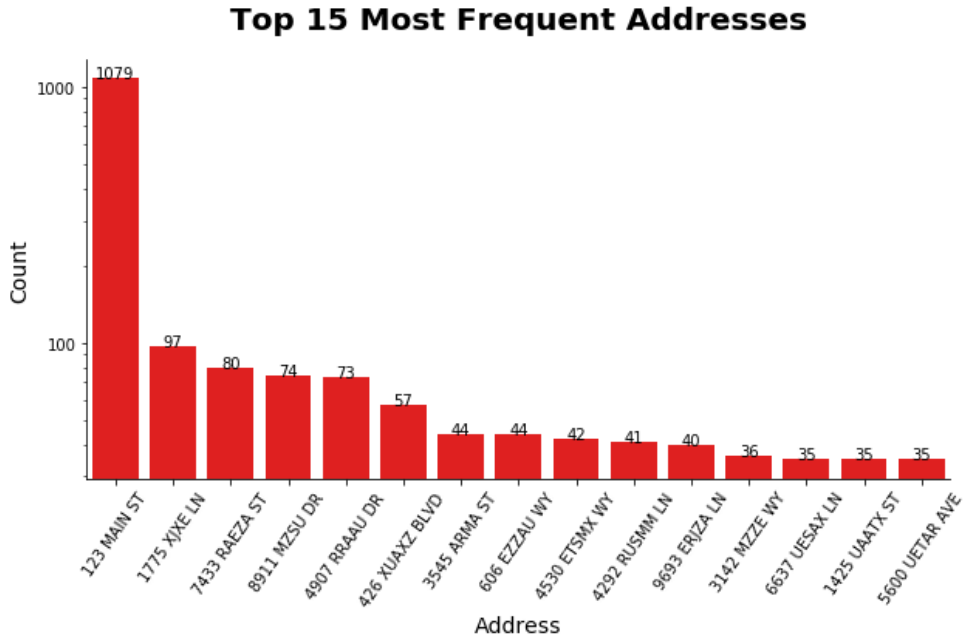

Field 4:
Name: firstname
Description: First name of the applicant



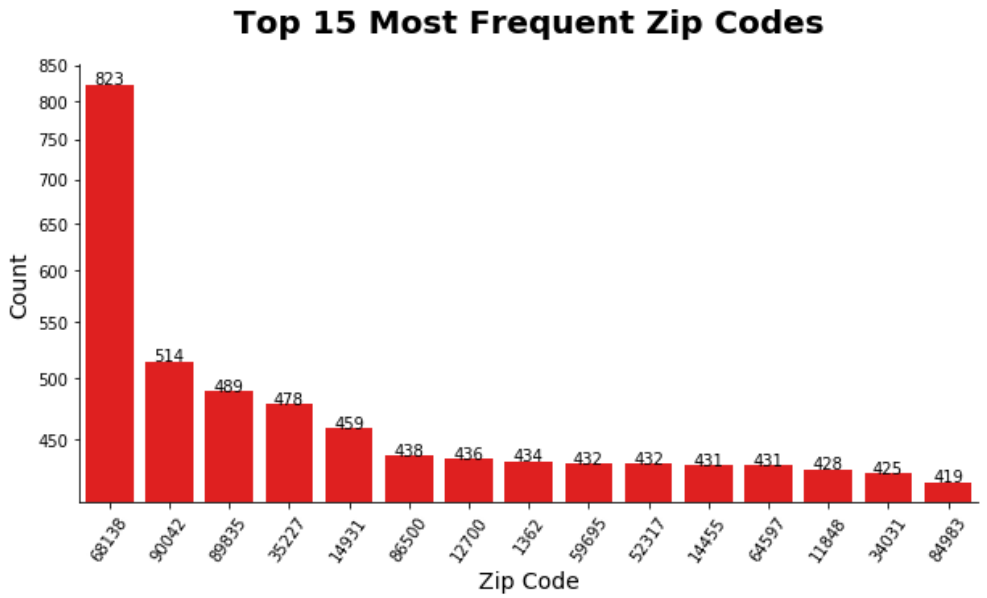
Field 5:
Name: lastname
Description: Last name of the applicant



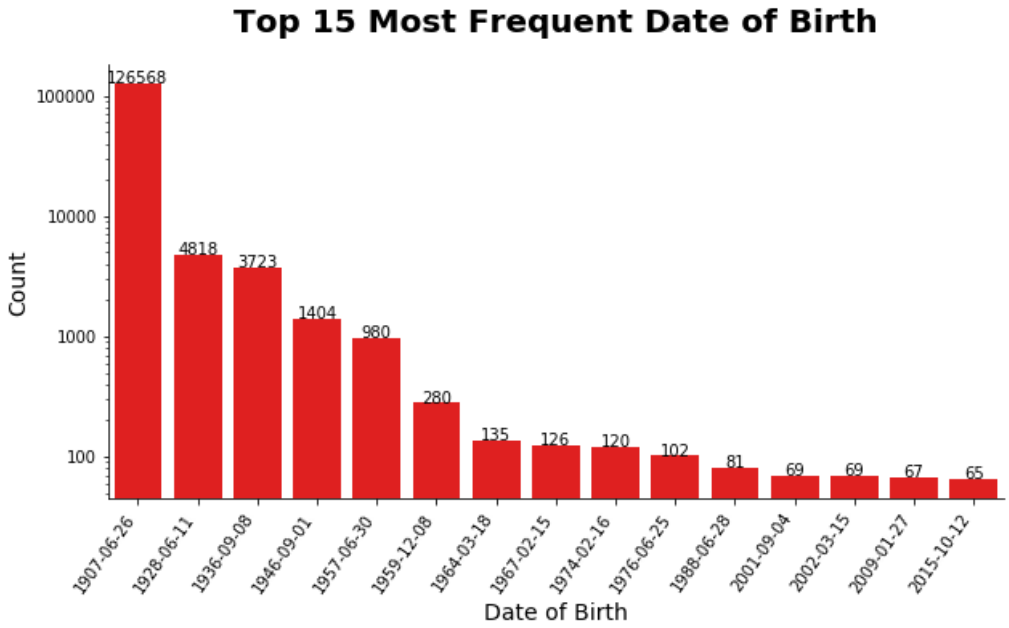

Field 6:
Name: address
Description: Address of the applicant

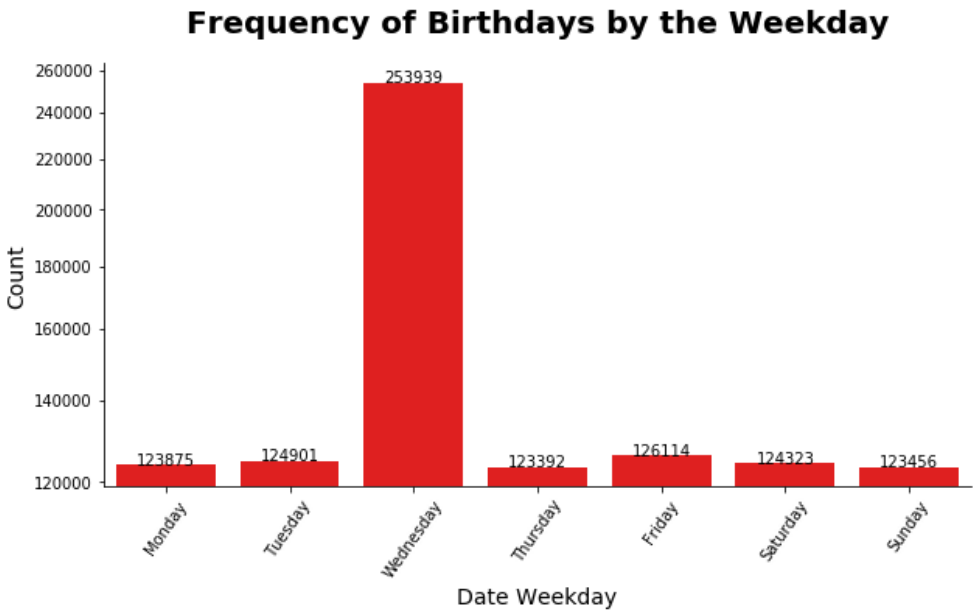


Field 7:
Name: zip5
Description: Postal code of the applicant

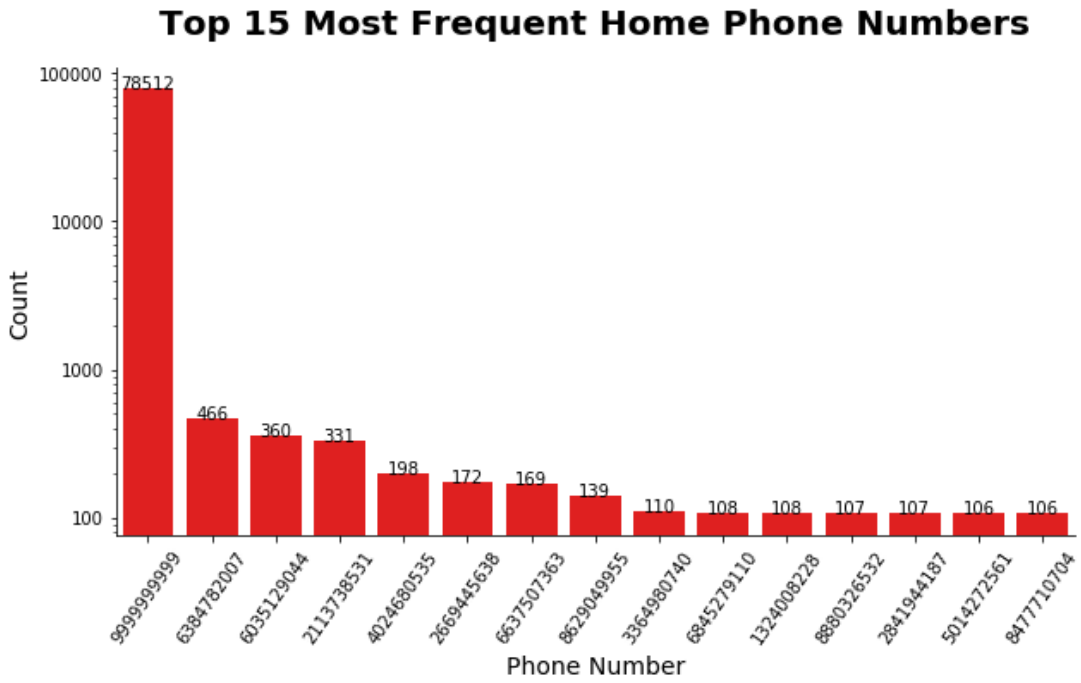



Field 8:
Name: dob
Description: Date of birth of the applicant

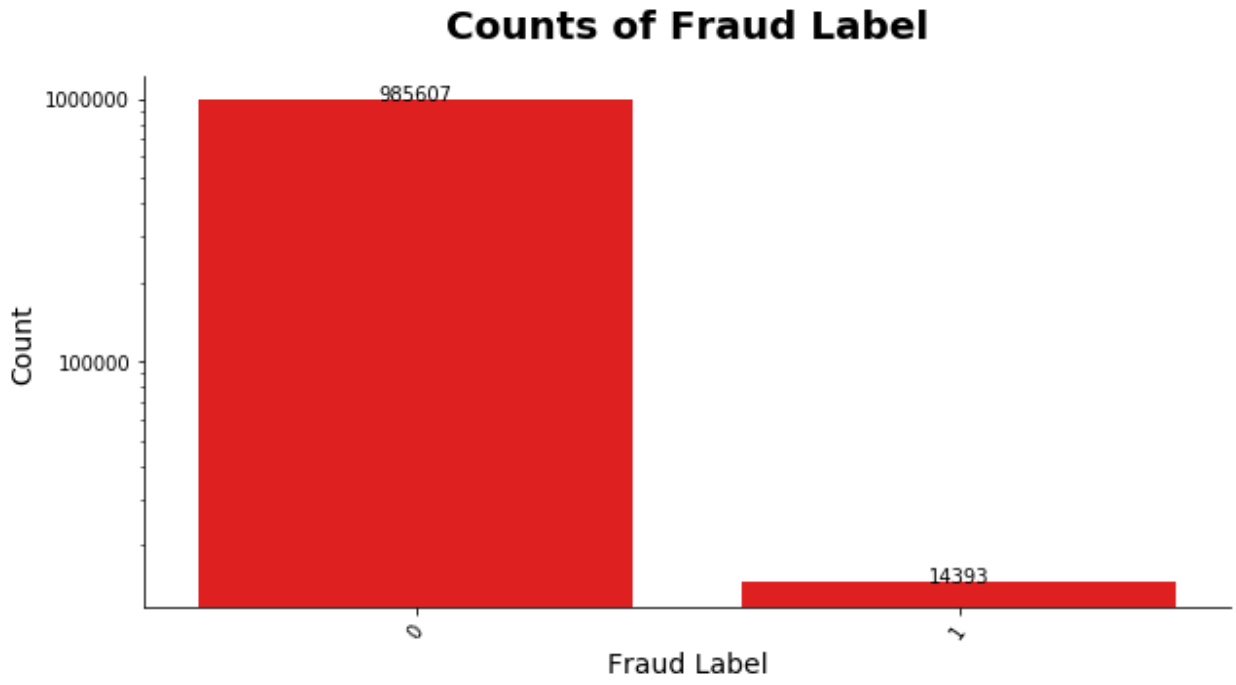





Field 9:
Name: homephone
Description: Home phone number of the applicant



Field 10:
Name: fraud_label
Description: Binary label for each record in the data to classify fraud vs no fraud



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| 46 | name_dob_count_30 |
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# Model Hyperparameters Performance

| Model | Parameters | | | | | | | Average FDR at 3% | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Iteration | Sampling Strategy (Majority:Minority) | penalty | C | solver | | | Train | Test | OOT |
| Logistic Regression | 1 | No Sampling | l2 | 1 | liblinear | | | 52.51 | 52.14 | 50.00 |
| | 2 | Class weight Argument (10:1) | l2 | 1 | liblinear | | | 52.81 | 52.48 | 50.84 |
| | 3 | SMOTE (70:30) | l2 | 1 | liblinear | | | 53.50 | 53.15 | 51.30 |
| | 4 | SMOTE (60:40) | l2 | 1 | liblinear | | | 53.94 | 53.41 | 51.30 |
| | 5 | SMOTE (50:50) | l2 | 1 | liblinear | | | 53.95 | 53.41 | 51.30 |
| | 6 | Undersample (70:30) | l2 | 1 | liblinear | | | 54.43 | 53.92 | 52.14 |
| | 7 | Undersample (60:40) | l2 | 1 | liblinear | | | 54.20 | 53.88 | 52.14 |
| | 8 | Undersample (50:50) | l2 | 1 | liblinear | | | 54.53 | 53.85 | 52.10 |
| | 9 | No Sampling | l2 | 0.1 | saga | | | 54.55 | 53.82 | 51.72 |
| | 10 | Undersample (70:30) | l2 | 0.1 | saga | | | 54.65 | 53.92 | 52.10 |
| | 11 | SMOTE (70:30) | l2 | 0.1 | saga | | | 54.14 | 53.55 | 51.26 |
| | 12 | No Sampling | l2 | 0.01 | lbfgs | | | 53.33 | 52.54 | 50.80 |
| | 13 | Undersample (70:30) | l2 | 0.01 | lbfgs | | | 53.89 | 53.18 | 51.34 |
| XGBoost | Iteration | Sampling Strategy (Majority:Minority) | learning_rate | n_estimators | max_depth | subsample | | Train | Test | OOT |
| | 1 | No Sampling | 0.1 | 400 | 3 | 1 | | 57.61 | 55.22 | 53.31 |
| | 2 | Scale Pos Weight = 10 | 0.1 | 400 | 3 | 1 | | 62.56 | 55.02 | 53.02 |
| | 3 | SMOTE (70:30) | 0.1 | 400 | 3 | 1 | | 58.28 | 54.89 | 49.75 |
| | 4 | Undersample (70:30) | 0.1 | 400 | 3 | 1 | | 57.33 | 54.89 | 52.85 |
| | 5 | No Sampling | 0.05 | 500 | 5 | 0.7 | | 56.92 | 55.35 | 53.1 |
| | 6 | No Sampling | 0.1 | 750 | 5 | 0.8 | | 59.49 | 55.02 | 52.68 |
| | 7 | No Sampling | 0.1 | 750 | 5 | 1 | | 58.54 | 54.92 | 53.1 |
| | 8 | No Sampling | 0.01 | 1000 | 3 | 1 | | 55.65 | 55.29 | 53.25 |
| | 9 | No Sampling | 0.1 | 600 | 3 | 0.8 | | 57.04 | 55.46 | 53.19 |
| | 10 | No Sampling | 0.05 | 600 | 5 | 1 | | 57.11 | 55.05 | 53.44 |
| Random Forest | Iteration | Sampling Strategy (Majority:Minority) | criterion | n_estimators | max_depth | min_samples_split | | Train | Test | OOT |
| | 1 | No Sampling | gini | 100 | 20 | 300 | | 55.59 | 55.06 | 53.35 |
| | 2 | Class Weight Argument (10:1) | gini | 100 | 20 | 300 | | 55.66 | 55.09 | 53.56 |
| | 3 | SMOTE (70:30) | gini | 100 | 20 | 300 | | 55.75 | 55.09 | 51.55 |
| | 4 | Undersample (70:30) | gini | 100 | 20 | 300 | | 55.38 | 54.6 | 52.98 |
| | 5 | Class Weight Argument (10:1) | entopry | 150 | 10 | 200 | | 55.51 | 54.76 | 53.35 |
| | 6 | Class Weight Argument (10:1) | entopry | 150 | 25 | 300 | | 55.73 | 55.06 | 53.48 |
| | 7 | Class Weight Argument (10:1) | entopry | 150 | 30 | 400 | | 55.67 | 55.12 | 53.52 |
| | 8 | Class Weight Argument (10:1) | gini | 100 | 20 | 400 | | 55.71 | 55.12 | 53.52 |
| | 9 | Class Weight Argument (10:1) | gini | 50 | 25 | 300 | | 55.65 | 55.06 | 53.44 |
| | 10 | Class Weight Argument (10:1) | gini | 50 | 25 | 300 | | 55.69 | 54.99 | 53.56 |
| Neural Networks | Iteration | Sampling Strategy (Majority:Minority) | optimizer | layers | nodes | epochs | activation | Train | Test | OOT |
| | 1 | No Sampling | adam | 1 | 20 | 10 | relu | 55.22 | 54.46 | 52.18 |
| | 2 | SMOTE (70:30) | adam | 1 | 20 | 10 | relu | 55.6 | 54.73 | 52.56 |
| | 3 | Undersample (70:30) | adam | 1 | 20 | 10 | relu | 54.44 | 54.14 | 52.01 |
| | 4 | SMOTE (70:30) | sgd | 1 | 10 | 20 | relu | 54.47 | 54.01 | 52.05 |
| | 5 | SMOTE (70:30) | sgd | 1 | 30 | 20 | relu | 55.25 | 54.53 | 52.31 |
| | 6 | SMOTE (70:30) | sgd | 1 | 30 | 30 | relu | 55.25 | 54.53 | 52.26 |
| | 7 | SMOTE (70:30) | adam | 1 | 50 | 30 | relu | 55.59 | 54.73 | 53.19 |
| | 8 | SMOTE (70:30) | adam | 1 | 30 | 40 | relu | 55.59 | 55.09 | 52.72 |
| | 9 | SMOTE (70:30) | adam | 1 | 50 | 40 | relu | 55.72 | 55.12 | 53.02 |
| | 10 | SMOTE (70:30) | adam | 1 | 50 | 20 | relu | 55.61 | 54.76 | 53.23 |