APPLICATION FRAUD ANALYSIS REPORT

Akshay Bhide, Suhas Sridhar, Puneet Singh Maini, Siddharth Sharma, Vaibhav Jha, Mane Mirijanyan

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Professor Stephen Coggeshall
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EXECUTIVE SUMMARY

The focus of this report is to examine the application dataset in order to identify the fraud activity using supervised machine learning methods. This was a supervised problem since the data included a column that indicated whether an application was fraudulent or not. It also contained a number of other identifying data fields about the applicant, such as the SSN, address, or phone number used. The dataset had 1,000,000 records and 10 data fields.

The steps we took were:

1. An analysis of each of the 10 fields with accompanying visualizations to better understand how each of the fields are distributed.
2. Addressing frivolous values in the SSN, address, homephone, and DOB fields.
3. Creating a number of variables (1155) across categories like “days since last seen”, ”velocity”, ”relative velocity” and “count by entities”.
4. Splitting the dataset into training, testing and out-of-time dataset, with the out-of-time section constituting the last two months of data.
5. Feature selection on training and testing data using “Kolmogorov-Smirnov” (KS) and Fraud Detection Rate (FDR) at 3% to select the best 30 variables.
6. Building several fraud detection models using the 30 variables, including Logistic Regression, Booster Trees, Random Forests, Decision Trees, and neural networks. The models were also parameter tuned to get the best results.

After analyzing 30 variables and supervised machine learning algorithms, we found that Neural Network had the best performance. This model caught 53.73% of the frauds with a 3%FDR.

DATA DESCRIPTION

Analysis in this report is using a data set that contains information of the people who filed their applications for a product. It contains fields like Social Security number, the date on which the application was filled, applicants first name, last name, address, and DOB. The distribution of data fields and the linkage properties of the dataset are representative of realistic US product application data despite the fact that it has been generated synthetically.

Among the interesting features of the dataset is that each record is labeled (i.e. classified) with either a 1 or a 0 in the "fraud_label" data field.A record containing a label of 1 was considered a fraudulent application record, while a record containing a label of 0 was considered a legitimate application record.

Time Period: 1st January 2016 – 31st December 2016

No of fields: 10

No of Records: 1,000,000

Table 1: Categorical Variables

Field Name	% Populated	# Unique Values	Most Common Value
Record	100%	1,000,000	NA
SSN	100%	835,819	9999999999
Firstname	100%	78,136	EAMSTRMT
Lastname	100%	177,001	ERJSAXA
Address	100%	828,774	123 MAIN ST
Zip5	100%	26,370	68138
Homephone	100%	28,244	9999999999
Fraud_label	100%	2	0

Table 2: Date Variables

Field Name	% Populated	Min	Max	Mean	Stdev	% Zero
Date	100%	2016-01-01	2016-12-31	NA	NA	0
DOB	100%	1900-01-01	2016-10-31	NA	NA	0

Based on our analysis of the ten raw data fields, the most critical fields in detecting potential fraud cases were the one relating to the social security number code, the date field, the address field, and the date of birth field. In the following, we present some of the relevant aspects of the critical data fields. Please refer to Appendix A for the Data Quality Report (DQR) for a more complete description of all of the data fields.

SSN

A 9-digit categorical data field containing the social security number (SSN) of the applicant. There are 835,319 unique values for this field and the most common value for SSN is 999-99-9999. Also, for SSN entries that have less than 9 digits, those entries have a leading zero(s). The bar charts below show the top 20 "ssn" data field values.

Date

A numerical field mentioning the date on which the application was filed. The table below gives the details of the Top 20 dates on which the maximum number of applications were received and the graph to its right presents the number of applications received on a monthly basis.

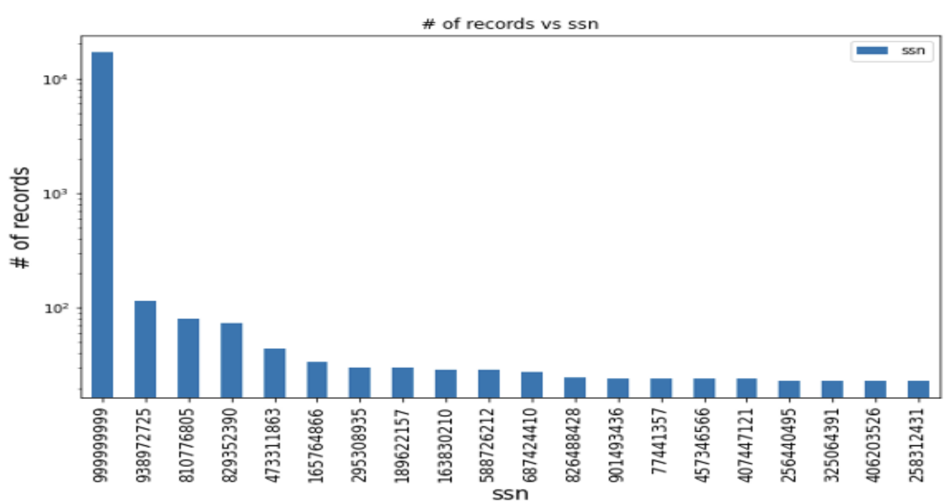
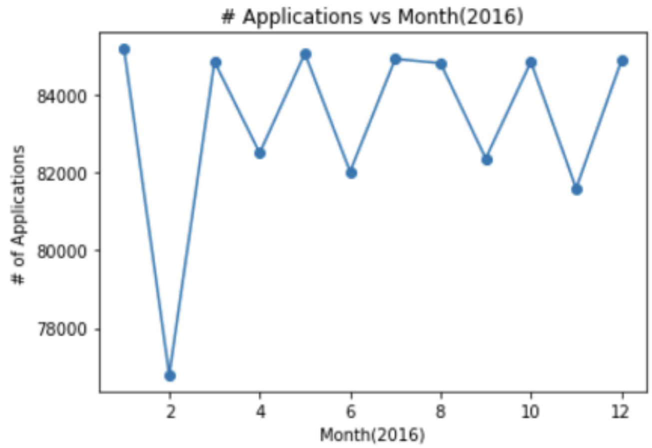


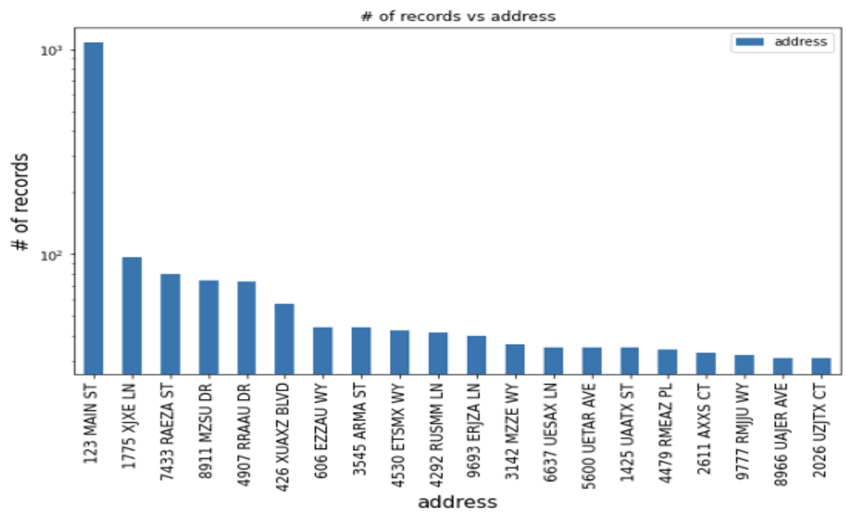
Table 3: Date and Application Count

Date	Count
16-Aug-16	2877
4-Mar-16	2861
18-Jul-16	2849
17-Apr-16	2848
1-Jan-16	2840
3-Sep-16	2832
8-Aug-16	2832
28-Dec-16	2832
27-Aug-16	2831
6-Oct-16	2831
9-Jun-16	2831
7-Mar-16	2831
4-Aug-16	2828
13-Mar-16	2826
16-Jan-16	2819
14-Jul-16	2818
30-Mar-16	2818
23-Aug-16	2817
6-Dec-16	2815
24-Oct-16	2814



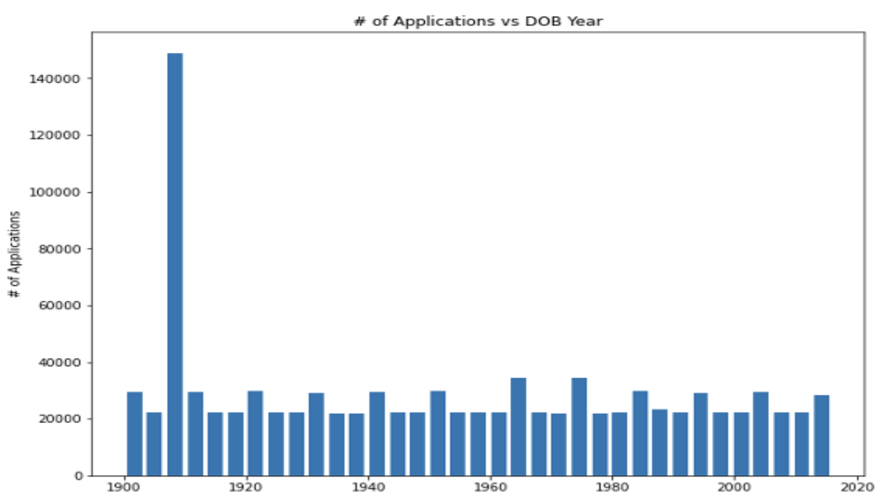
Address

A categorical field that gives the address of each applicant who has applied for the product. There are 828,774 unique values for this field, and the most common street address is 123 Main St.



DOB

A numerical field that gives details of the Date of Birth of each applicant. The most common date of birth for applications is June 26, 1907.



Data Cleaning

Although 100% of the data fields were populated, we discovered four fields contained frivolous values.

Table 4: Frivolous Values in dataset

Data Field	Frivolous Value	# of Records
SSN	999999999	16,935
Address	123 Main St	1,079
DOB	19070626	126,568
Homephone	9999999999	78,512

It is imperative to clean a dataset containing frivolous values before conducting an analysis to avoid resulting in false conclusions and erroneous results.

There are different methods that can be employed to get rid of frivolous values. Using a unique set of values, was our chosen method for cleaning these values. For instance, if an application record had a value of "999999999" in the "ssn" data field and a value of "123 MAIN ST" in the "address" data field, then the record number was used to replace the frivolous values in both the "ssn" and "address" data fields. This method was used for all frivolous values in the dataset until the dataset was completely free and clear of frivolous values.

Furthermore, some of the data in the fields ssn ,address, homephone, dob and zip did not meet the minimum character requirement. Zip codes, for instance, should contain five characters, but some records had a four- or three-character zip code. In order to make data points consistent with the other data in the field, we added zeroes to these data points. For example, a zip code entered as "2765" becomes "02765". The same method was used for all other fields as well.

```
# fix frivolous values

#ssn
df.loc[df.ssn == 999999999, 'ssn'] = -df[df.ssn==999999999]['record']
df['ssn'] = df['ssn'].apply(lambda x: '{0:0>9}'.format(x))

#address
df.loc[df.address=='123 MAIN ST', 'address'] = \
    df.loc[df.address=='123 MAIN ST', 'record'].apply(lambda x: str(x) + ' RECORD')

#dob
df.loc[df.dob==19070626, 'dob'] = -df.loc[df.dob==19070626]['record']
df['dob'] = df['dob'].apply(lambda x: '{0:0>8}'.format(x))
#homephone
df.loc[df.homephone==9999999999, 'homephone'] = -df.loc[df.homephone==9999999999]['record']
df['homephone'] = df['homephone'].apply(lambda x: '{0:0>10}'.format(x))

#zip
df['zip5'] = df['zip5'].apply(lambda x: '{0:0>5}'.format(x))
```

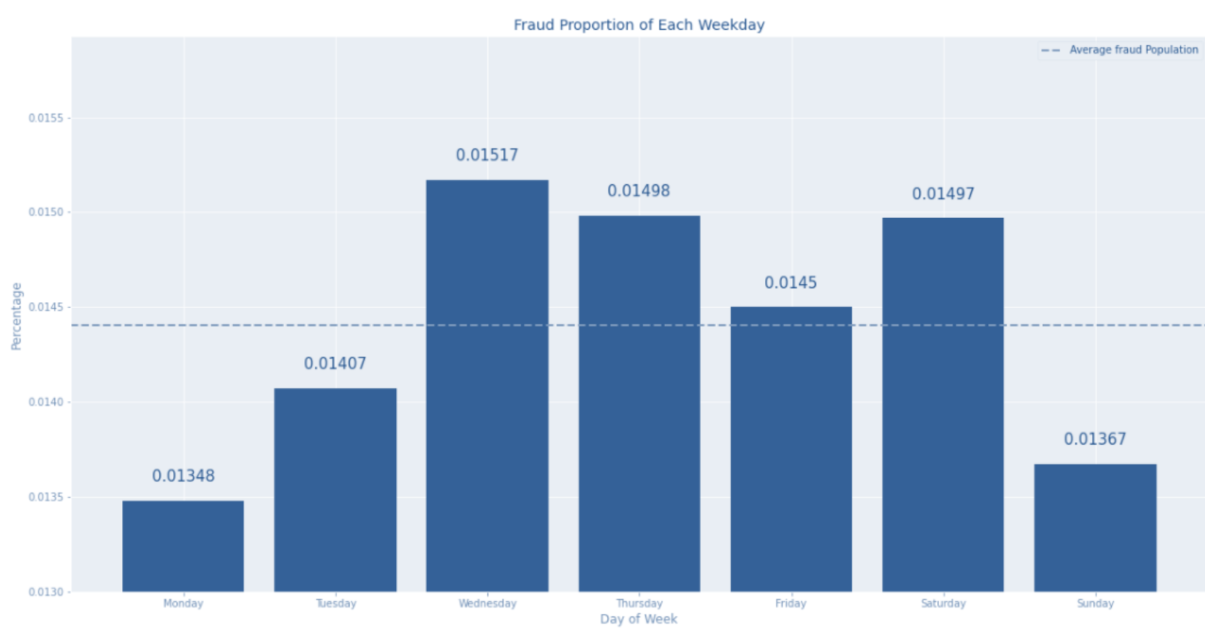
Candidate Variables

Age Group Risk:

Target encoded the fraud risk associated with the age-group of the applicant. The dob column was used to create 'age' after getting rid of the frivolous 'dob' values. Then, the missing 'age' was imputed using the mean age for that particular 'zip'. Further, missing values were imputed using the global mean of the 'age' columns (only 492 such records). These ages were binned into 4 categories - 'young', 'adult', 'old', 'very_old'. Then the fraud_risk was calculated for each of these groups, smoothened and stores as 'Age_group_risk'

Risk Table:

Risk table variable "dow_risk" using a target encoding method to represent each day of the week with the average of fraud labels on that day. To avoid a few samples in one category, we also implement statistically smoothing to smooth the data. The idea is to check if there is a higher fraud proportion on any one of these weekdays.



"Core Relationship" Variables:

These are the basic combinations of existing columns in the original dataset. These variables are used to create "entities" through various combinations to create other variables. We created 16 core relationship variables**.**

"Days Since Last Seen" Variables:

An important indicator of fraud records is the frequency of occurrence of specific identity information. For instance, if the same SSN occurs in the applications every day, it can't be not suspicious. Hence, for those 29 main fields, we created 29 "days since last seen" variables, which showed the number of days since the last time the same record appeared. If it never appeared before, we just fill it with 365 because in this case, a larger number means lower frequency, which is less risky.

"Velocity" Variables:

In addition to monitoring the frequency in 10 months, we also pay attention to the velocity of records in a shorter time range like 3 days or 7 days to narrow the scope and make better sense in a specific period. Hence, we decided to focus on finding the number of records seen over the past 0, 1, 3, 7, 14, 30 days (0 means today) grouped by each given entity. Since we have 29 main entities and combination groups and 6 different time periods to consider, We got 174 (29*6) new "velocity" variables.

"Relative Velocity" Variables:

We also wanted to investigate whether the velocity of a variable in the short-term was expected in comparison to its velocity in the long-term. In this case, relative velocity was calculated by dividing the number of occurrences of the entity or entity combination in the recent past, namely the same day or the past 1 day, by its average daily appearance over the longer term (see the formula). The longer-term is defined as a time frame of 3, 7, 14, or 30 days. The same entity and entity combinations used in creating the velocity variables were used here.

$$\frac{\text{\# apps with that } \textbf{\textit{entity}} \text{ seen in the recent past } \{0, 1\} \text{ days}}{\text{\# apps with that } \textbf{\textit{same entity}} \text{ seen in the past} \{3, 7, 14, 30\} \text{ days}}$$

"Counts by entities" variables:

Other than evaluating the records by frequency, it is also important to check whether the same piece of information such as SSN is used by different fraudsters to make up disparate identities. Based on this observation, we designed a variable that counts the number of different values for an entity or combination group in all those past records that have the same value for another entity or combination group. For example, the number of different addresses associated with the same SSN. 792 variables were created.

In total, 1155 variables were created.

FEATURE SELECTION

After creating the 1155 candidate variables we plan to use for our fraud analysis, we want to find which of these variables are most informative towards fraud and only use those. The feature selection process will allow for a reduction in dimensionality (helping with the curse of dimensionality), while also ensuring the data that is kept is meaningful and contributes significantly towards our final goal of accurately detecting fraud. The process that was followed was to first use a filter and then a wrapper.

Filter

Using a filter is a fast and easy way to go from thousands of candidate variables to hundreds, finding the variables that on their own contribute the best towards detecting fraud. This filter calculated a simple univariate KS score, which essentially calculates the separation between "goods" and "bads" for a single candidate variable. The variables with the highest KS scores have the most separation in these two distributions, and the top 150 out of the 1155 candidate variables were passed into a wrapper.

Wrapper

The wrapper was used to go from the 150 to the final 30 variables that were going to be passed into our models. Out of the 3 most common wrapper methods, forwards selection was chosen. Forward selection starts with an empty set of variables, then builds n separate 1-dimensional models (a simple Random Forest Classifier was used to evaluate performance) and keeps the top variable. At each subsequent step, variables that haven't been chosen are added to a model with the chosen one-at-a-time, keeping the best performing variable every step. This process stops when 30 variables have been chosen, and below is those 30 variables, listed in rank order by multivariate importance.

FINAL MODEL VARIABLES AND DESCRIPTIONS

The below list shows the variables ordered by rank and their descriptions

1. fulladdress_count_30
    - the number of applications with an identical "**fulladdress**" value over the past **30** days from when the application was submitted
2. ssn_dob_count_30
    - the number of applications with an identical "**ssn_dob**" value over the past **30** days from when the application was submitted
3. homephone_count_3
    - the number of applications with an identical "**homephone**" value over the past **3** days from when the application was submitted
4. fulladdress_unique_count_for_dob_homephone_60
    - the number of unique "**fulladdress**" values for that application's particular "**dob_homephone**" value over the past **60** days from when the application was submitted
5. name_dob_count_30
    - the number of applications with an identical "**name_dob**" value over the past **30** days from when the application was submitted
6. fulladdress_unique_count_for_ssn_homephone_30
    - the number of unique "**fulladdress**" values for that application's particular "**ssn_homephone**" value over the past **30** days from when the application was submitted
7. fulladdress_unique_count_for_ssn_homephone_60
    - the number of unique "**fulladdress**" values for that application's particular "**ssn_homephone**" value over the past **60** days from when the application was submitted
8. ssn_name_count_30
    - the number of applications with an identical "**ssn_name**" value over the past **30** days from when the application was submitted
9. name_dob_count_7
    - the number of applications with an identical "**name_dob**" value over the past **7** days from when the application was submitted
10. fulladdress_unique_count_for_name_dob_30
    - the number of unique "**fulladdress**" values for that application's particular "**name_dob**" value over the past **30** days from when the application was submitted
11. fulladdress_homephone_count_30

    - the number of applications with an identical “**fulladdress_homephone**” value over the past **7** days from when the application was submitted
12. fulladdress_unique_count_for_ssn_name_30
    - the number of unique “**fulladdress**” values for that application’s particular “**ssn_name**” value over the past **30** days from when the application was submitted
13. fulladdress_unique_count_for_fulladdress_dob_30
    - the number of unique “**fulladdress**” values for that application’s particular “**fulladdress_dob**” value over the past **30** days from when the application was submitted
14. fulladdress_unique_count_for_ssn_name_dob_30
    - the number of unique “**fulladdress**” values for that application’s particular “**ssn_name_dob**” value over the past **30** days from when the application was submitted
15. fulladdress_unique_count_for_ssn_30
    - the number of unique “**fulladdress**” values for that application’s particular “**ssn**” value over the past **30** days from when the application was submitted
16. address_count_0_by_30
    - the number of applications with an identical “**address**” value seen today divided by the number of applications with an identical “**address**” value over the past **30** days
17. address_count_0
    - the number of applications with an identical “**address**” value in the same day as when the application was submitted
18. ssn_firstname_count_30
    - the number of applications with an identical “**ssn_firstname**” value over the past **30** days from when the application was submitted
19. ssn_dob_count_0_by_30
    - the number of applications with an identical “**ssn_dob**” value seen today divided by the number of applications with an identical “**ssn_dob**” value over the past **30** days
20. ssn_lastname_count_30
    - the number of applications with an identical “**ssn_lastname**” value over the past **30** days from when the application was submitted
21. ssn_firstname_count_7
    - the number of applications with an identical “**ssn_firstname**” value over the past **7** days from when the application was submitted
22. ssn_name_dob_count_0_by_30
    - the number of applications with an identical “**ssn_name_dob**” value seen today divided by the number of applications with an identical “**ssn_name_dob**” value over the past **30** days

23. fulladdress_unique_count_for_name_fulladdress_30
    - the number of unique "**fulladdress**" values for that application's particular "**name_fulladdress**" value over the past **30** days from when the application was submitted
24. ssn_count_30
    - the number of applications with an identical "**ssn**" value over the past **30** days from when the application was submitted
25. ssn_name_dob_count_30
    - the number of applications with an identical "**ssn_name_dob**" value over the past **30** days from when the application was submitted
26. fulladdress_count_0_by_30
    - the number of applications with an identical "**full_address**" value seen today divided by the number of applications with an identical "**full_address**" value over the past **30** days
27. ssn_count_0_by_30
    - the number of applications with an identical "**ssn**" value seen today divided by the number of applications with an identical "**ssn**" value over the past **30** days
28. ssn_name_dob_count_0_by_14
    - the number of applications with an identical "**ssn_name_dob**" value seen today divided by the number of applications with an identical "**ssn_name_dob**" value over the past **14** days

29. ssn_dob_count_7
    - the number of applications with an identical "**ssn_dob**" value over the past **7** days from when the application was submitted
30. ssn_name_dob_count_14
    - the number of applications with an identical "**ssn_name_dob**" value over the past **14** days from when the application was submitted.

Model Algorithms

After the top 30 variable selection, our team applied multiple supervised machine learning algorithms in order to build the fraud detection models. The main goal was to catch the most fraudulent records from the top 3% of the whole dataset ranked by the model output.

High level summary of the process to went through:

1. In order to build the fraud detection models, employed the following algorithms:
    a. Logistic Regression
    b. Random Forest
    c. Boosted Tree
    d. Neural Networks
    e. Decision Tree
2. For each one of them, several models have been built, with a number of different values of parameters and the number of variables.
3. We split the data into 3 sets of testing data and training data for every model, in order to perform a 3-fold cross validation.
4. For each fold we trained the model with the training dataset. We also predicted the training, testing and OOT dataset outputs through application of the fitted model.
5. We sorted the output records in descending order. Afterwards, we computed the FDR using the following formula:

$$\text{FDR at 3\%} = \left(\frac{\textbf{Number of bad records in the top 3\% of the data}}{\textbf{Number of bad records in the dataset}} \right)$$

6. At 3% of FDR for training, testing and OOT datasets, we averaged the results derived from 3 folds respectively.
7. Last but not least, for the final fraud detection model, we chose the highest average FDR model.

Explanation of Algorithms

1. Logistic Regression

Logistic Regression is the baseline and most commonly used model to solve binary classification problems. It observes the relationship between dependent binary variable and independent variables. It returns an "S" shaped squiggle following a sigmoid function. The model can take any real-valued number and return an outcome that is in between 0 and 1.
We have chosen six parameters: penalty, C(regularization), solver, max_iter, multi_class and warm_start, and the results can be observed below.

The following combinations were used to build various logistic regression models:

- Number of variables: 10, 20, 30
- Solver: liblinear, lbfgs
- Penalty: l1, l2
- C(regularization): 0.1, 1

Table 4: Average FDR at 3% using Logistic Regression

Model	Parameters				Average FDR at 3%		
Logistic Regression	# of variables	solver	penalty	C	Train	Test	OOT
1	10	liblinear	l1	0.1	52.265	52.151	50.978
2	20	liblinear	l1	1	53.197	52.961	51.313
3	30	lbfgs	l2	1	52.174	54.532	50.964
4	10	lbfgs	l2	1	53.197	52.928	51.285
5	20	liblinear	l1	0.1	53.107	52.336	51.021
6	30	lbfgs	l2	0.1	52.426	52.529	50.936

2. Random Forest

Random Forest is a group learning method applied for classification and regression problems. It applies bootstrapped samples from a dataset together with a subset of variables to come up with decision trees. It controls the overfitting problem through random selection of a subset of all attributes every time a decision tree is being built.

The following combinations were used to build various random forest models:

- Number of variables: 30
- Number of trees: 100, 150, 200, 250
- Max_features: 7
- Max_depth: 60, 70, 80

Table 5: Average FDR at 3% using Random Forest

Random Forest	# of variables	# of trees	Max features	Max depth	Train	Test	OOT
1	30	100	7	60	56.316	55.268	53.813
2	30	100	7	70	56.316	55.268	53.813
3	30	100	7	80	56.316	55.295	53.982
4	30	150	7	60	56.292	55.376	53.813
5	30	150	7	70	56.316	55.268	53.856
6	30	150	7	80	56.316	55.295	53.898
7	30	200	7	60	56.316	55.295	53.856
8	30	200	7	70	56.304	55.268	53.856
9	30	200	7	80	56.304	55.295	53.814
10	30	250	7	60	56.304	55.322	53.856
11	30	250	7	70	56.316	55.349	53.856
12	30	250	7	80	56.316	55.376	53.856

3. Boosted Trees

Boosted trees are sequences of decision trees that are implemented to improve the prediction result. The primary method is iteratively training a series of weak learners in order to result in a strong learner. The ultimate goal is to minimize the residual error to increase the accuracy and improve the prediction.
We have used 100 and 400 for the number of estimators, as it is common to add more trees until no further improvements are identified. Adding more trees helps to slow down the overfitting. The learning rates are 0.1 and 0.01, as taking small incremental steps prevents overfitting and increases the chance for better accuracy on the testing data. We multiplied the prediction by learning rate to slow down the fitting process.

The following combinations were used to build various boosted tree models:

- Number of variables: 10, 20, 30
- Max_depth: 3, 7, 8
- Learning_rate: 0.1, 0.01
- Num_leaves: 7, 120, 250
- N_estimators: 100, 800

Table 6: Average FDR at 3% using Boosted Tree

Boosted Trees	# of variables	max_depth	Learning_rate	num_leaves	n_estimators	Train	Test	OOT
1	10	3	0.1	7	100	55.997	55.985	53.772
2	20	3	0.1	7	100	55.895	55.827	53.716
3	20	7	0.1	120	800	56.076	55.853	53.674
4	30	7	0.1	120	100	55.924	56.145	53.744
5	30	8	0.01	250	800	55.948	56.073	53.660

4. Neural Networks

In the scope of fraud detection, we also referred to more advanced machine learning algorithms like neural networks. It is a supervised learning algorithm that takes function R(m) -> R(o), where m is the number of input dimensions and o is the number for output dimensions. There can be one or more non-linear (hidden) layers in this model.

The following combinations were used to build various neural networks models:

- Number of variables: 10, 20, 30
- Solver: adam
- Learning_rate: constant, adaptive
- Layers: 1, 2, 3
- Hidden_layer_sizes (10, 15,10), (20, 20), (25, 10), (100)

Table 7: Average FDR at 3% using Neural Networks

Neural Network	# of variables	Solver	Learning rate	Layers	Hidden_layer_sizes	Train	Test	OOT
1	10	adam	constant	3	(10,15,10)	56.049	55.502	53.577
2	20	adam	constant	1	(100,)	55.869	55.789	53.549
3	20	adam	constant	2	(20,20)	55.666	56.193	53.632
4	30	adam	constant	2	(25,10)	57.109	56.801	54.802
5	20	adam	adaptive	1	(100,)	55.889	55.708	53.577

5. Decision Tree

Decision tree is a non-parametric supervised learning method that is applied for both regression and classification problems. The primary goal is to come up with a model that predicts the outcome by learning through basic decision rules taken from data.

The following combinations were used to build various decision tree models:

- Number of Variables: 30
- Max_depth: None, 20
- Criterion: gini
- Min_samples_leaf: 1, 60, 79
- Min_samples_split: 2, 300, 310, 1350
- Splitter: best, random

Table 8: Average FDR at 3% using Decision Tree

Decision Trees	# of variables	max_depth	criterion	min_samples_leaf	min_samples_split	splitter	Train	Test	OOT
1	30	None	gini	1	2	best	56.089	55.182	52.934
2	30	20	gini	60	310	random	55.965	55.751	53.545
3	30	20	gini	60	300	best	55.932	56.078	53.772
4	30	None	gini	79	1350	random	55.843	55.818	53.662

RESULTS

Based on all the models we built, NN has the best performance, which gave us an average FDR at 3% of 53.73%. Our final model is shown below. Table 6 to Table 8 show the detailed performance of this final model.

Table 9: Training Data Model Performance

Train	# Records	# Goods	# Bads	Fraud Rate								
	583454	575028	8426	0.014653								
	Bin Statistics					Cumulative Statistics						
Population Bin %	# recs	# goods	# bads	% goods	% bads	total	cum goods	cum bads	% cum goods	FDR	KS	FPR
1	5835	1439	4396	24.66	75.34	5835	1439	4396	0.25	52.31	52.06	0.33
2	5834	5628	206	96.47	3.53	11669	7067	4602	1.23	54.77	53.54	1.54
3	5835	5746	89	98.47	1.53	17504	12813	4691	2.23	55.83	53.60	2.73
4	5834	5793	41	99.30	0.70	23338	18606	4732	3.24	56.31	53.08	3.93
5	5835	5770	65	98.89	1.11	29173	24376	4797	4.24	57.09	52.85	5.08
6	5834	5782	52	99.11	0.89	35007	30158	4849	5.24	57.71	52.46	6.22
7	5835	5784	51	99.13	0.87	40842	35942	4900	6.25	58.31	52.06	7.34
8	5834	5769	65	98.89	1.11	46676	41711	4965	7.25	59.09	51.83	8.40
9	5835	5797	38	99.35	0.65	52511	47508	5003	8.26	59.54	51.28	9.50
10	5834	5791	43	99.26	0.74	58345	53299	5046	9.27	60.05	50.78	10.56
11	5835	5792	43	99.26	0.74	64180	59091	5089	10.28	60.56	50.29	11.61
12	5834	5795	39	99.33	0.67	70014	64886	5128	11.28	61.03	49.74	12.65
13	5835	5798	37	99.37	0.63	75849	70684	5165	12.29	61.47	49.17	13.69
14	5835	5801	34	99.42	0.58	81684	76485	5199	13.30	61.87	48.57	14.71
15	5834	5787	47	99.19	0.81	87518	82272	5246	14.31	62.43	48.12	15.68
16	5835	5793	42	99.28	0.72	93353	88065	5288	15.31	62.93	47.62	16.65
17	5834	5792	42	99.28	0.72	99187	93857	5330	16.32	63.43	47.11	17.61
18	5835	5796	39	99.33	0.67	105022	99653	5369	17.33	63.89	46.56	18.56
19	5834	5798	36	99.38	0.62	110856	105451	5405	18.34	64.32	45.98	19.51
20	5835	5788	47	99.19	0.81	116691	111239	5452	19.34	64.88	45.54	20.40

Table 10: Test Data Model Performance

Test	# Records	# Goods	# Bads	Fraud Rate								
	250053	246472	3581	0.014321								
	Bin Statistics					**Cumulative Statistics**						
Population Bin %	**#recs**	**#goods**	**#bads**	**%goods**	**%bads**	**total**	**cum goods**	**cum bads**	**% cum goods**	**FDR**	**KS**	**FPR**
1	2501	589	1912	23.55	76.45	2501	589	1912	0.24	53.05	52.81	0.31
2	2500	2415	85	96.60	3.40	5001	3004	1997	1.22	55.41	54.19	1.50
3	2501	2478	23	99.08	0.92	7502	5482	2020	2.22	56.05	53.82	2.71
4	2500	2487	13	99.48	0.52	10002	7969	2033	3.23	56.41	53.18	3.92
5	2501	2483	18	99.28	0.72	12503	10452	2051	4.24	56.91	52.67	5.10
6	2500	2473	27	98.92	1.08	15003	12925	2078	5.24	57.66	52.41	6.22
7	2501	2487	14	99.44	0.56	17504	15412	2092	6.25	58.05	51.79	7.37
8	2500	2482	18	99.28	0.72	20004	17894	2110	7.26	58.55	51.29	8.48
9	2501	2473	28	98.88	1.12	22505	20367	2138	8.26	59.32	51.06	9.53
10	2500	2489	11	99.56	0.44	25005	22856	2149	9.27	59.63	50.35	10.64
11	2501	2489	12	99.52	0.48	27506	25345	2161	10.28	59.96	49.68	11.73
12	2500	2490	10	99.60	0.40	30006	27835	2171	11.29	60.24	48.94	12.82
13	2501	2489	12	99.52	0.48	32507	30324	2183	12.30	60.57	48.27	13.89
14	2500	2486	14	99.44	0.56	35007	32810	2197	13.31	60.96	47.65	14.93
15	2501	2479	22	99.12	0.88	37508	35289	2219	14.32	61.57	47.25	15.90
16	2500	2483	17	99.32	0.68	40008	37772	2236	15.33	62.04	46.72	16.89
17	2501	2487	14	99.44	0.56	42509	40259	2250	16.34	62.43	46.10	17.89
18	2501	2492	9	99.64	0.36	45010	42751	2259	17.35	62.68	45.33	18.92
19	2500	2483	17	99.32	0.68	47510	45234	2276	18.35	63.15	44.80	19.87
20	2501	2477	24	99.04	0.96	50011	47711	2300	19.36	63.82	44.46	20.74

Table 11: OOT Data Model Performance

OOT	# Records	# Goods	# Bads	Fraud Rate								
	166493	164107	2386	0.014331								
	Bin Statistics					Cumulative Statistics						
PopBin %	# recs	# goods	# bads	% goods	% bads	total	cum goods	cum bads	% cum goods	FDR	KS	FPR
1	1665	455	1210	27.33	72.67	1665	455	1210	0.28	50.71	50.44	0.38
2	1665	1612	53	96.82	3.18	3330	2067	1263	1.26	52.93	51.67	1.64
3	1665	1646	19	98.86	1.14	4995	3713	1282	2.26	53.73	51.47	2.90
4	1665	1650	15	99.10	0.90	6660	5363	1297	3.27	54.36	51.09	4.13
5	1665	1649	16	99.04	0.96	8325	7012	1313	4.27	55.03	50.76	5.34
6	1665	1650	15	99.10	0.90	9990	8662	1328	5.28	55.66	50.38	6.52
7	1665	1651	14	99.16	0.84	11655	10313	1342	6.28	56.24	49.96	7.68
8	1664	1647	17	98.98	1.02	13319	11960	1359	7.29	56.96	49.67	8.80
9	1665	1646	19	98.86	1.14	14984	13606	1378	8.29	57.75	49.46	9.87
10	1665	1649	16	99.04	0.96	16649	15255	1394	9.30	58.42	49.13	10.94
11	1665	1650	15	99.10	0.90	18314	16905	1409	10.30	59.05	48.75	12.00
12	1665	1648	17	98.98	1.02	19979	18553	1426	11.31	59.77	48.46	13.01
13	1665	1652	13	99.22	0.78	21644	20205	1439	12.31	60.31	48.00	14.04
14	1665	1650	15	99.10	0.90	23309	21855	1454	13.32	60.94	47.62	15.03
15	1665	1652	13	99.22	0.78	24974	23507	1467	14.32	61.48	47.16	16.02
16	1665	1655	10	99.40	0.60	26639	25162	1477	15.33	61.90	46.57	17.04
17	1665	1656	9	99.46	0.54	28304	26818	1486	16.34	62.28	45.94	18.05
18	1665	1650	15	99.10	0.90	29969	28468	1501	17.35	62.91	45.56	18.97
19	1665	1649	16	99.04	0.96	31634	30117	1517	18.35	63.58	45.23	19.85
20	1665	1649	16	99.04	0.96	33299	31766	1533	19.36	64.25	44.89	20.72

CONCLUSIONS

This report outlines an investigation into application fraud done with a year's worth of synthetic application data. After building a Data Quality Report, we cleaned the dataset, removing frivolous values. In the candidate variable creation process, we first created core relationship variables to capture relationships across fields and then created 1155 total candidate variables for this analysis. Afterwards, using a filter filtering by KS score and a wrapper performing forward selection with a RandomForestClassifier, we came to our final 30 model variables.

These variables were then used to train and test 5 different linear and nonlinear model types, tuning hyperparameters for each run to ultimately land on the best performing model: a neural net. This neural net model was then applied once again to the entire data set to generate the final results above, resulting in a 3% Fraud Detection Rate on the OOT data of 53.73%.

In terms of opportunities for future work, there are two main areas where we see the biggest opportunities for improvement. Primarily, access to domain experts would help with creating a more accurate list of initial candidate variables, and would also give us the opportunity to be able to check-in with them along the process of this project. Another area for improvement would be more time or computational resources. Specifically in creating candidate variables, considering how many variables to include in the wrapper during the feature selection process, and running various models, having more computational power would have allowed us to create more variables, pass more variables into our wrapper, and run more models. Finally, having access to more fields related to each application would allow us to not have to create more than 5-10 candidate variables centered around a single data field, allowing us to create a wider variety of variables which could perhaps have led to a more accurate final model.

APPENDIX A : DATA QUALITY REPORT

Summary

This data set contains information of the people who filed their applications for a product. It contains fields like Social Security number, the date on which the application was filled, applicants first name, last name, address, and DOB. It also contains a field called Fraud Label which classifies each record as to whether it is a fraud or not. However, this data is a synthetic dataset that has been made from the analysis of a few billion real US applications.

Time Period: 1st January 2016 – 31st December 2016
No of fields: 10
No of Records: 1,000,000

Summary Table

Brief Summary table for all the fields of the dataset are as given below:

Table 12: Summary table for categorical fields

Field Name	% Populated	# Unique Values	Most Common Value
Record	100%	1,000,000	NA
SSN	100%	835,819	9999999999
Firstname	100%	78,136	EAMSTRMT
Lastname	100%	177,001	ERJSAXA
Address	100%	828,774	123 MAIN ST
Zip5	100%	26,370	68138
Homephone	100%	28,244	9999999999
Fraud_label	100%	2	0

Table 13: Summary table for numerical fields

Field Name	% Populated	Min	Max	Mean	Stdev	% Zero
Date	100%	2016-01-01	2016-12-31	NA	NA	0
DOB	100%	1900-01-01	2016-10-31	NA	NA	0

Data Field Exploration

Field 1: Record

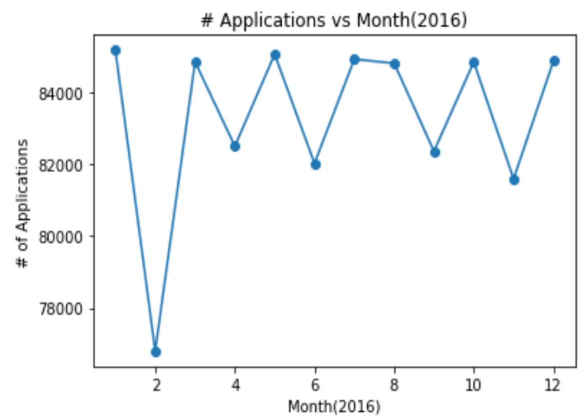
A categorical field with a unique integer value for each record from 1 to 1,000,000. As each value is unique, therefore we are not showing any visualization for it.

Field 2: Date

A numerical field mentioning the date on which the application was filed. The table below gives the details of the Top 20 dates on which the maximum number of applications were received and the graph to its right presents the no of applications received on a monthly basis.

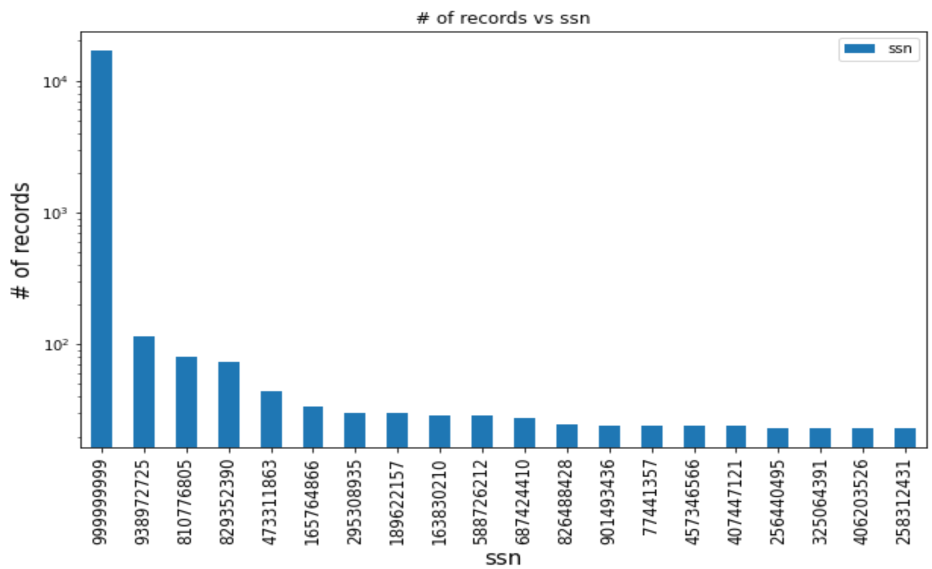
Table 14: Count of Top 20 dates

Date	Count
16-Aug-16	2877
4-Mar-16	2861
18-Jul-16	2849
17-Apr-16	2848
1-Jan-16	2840
3-Sep-16	2832
8-Aug-16	2832
28-Dec-16	2832
27-Aug-16	2831
6-Oct-16	2831
9-Jun-16	2831
7-Mar-16	2831
4-Aug-16	2828
13-Mar-16	2826
16-Jan-16	2819
14-Jul-16	2818
30-Mar-16	2818
23-Aug-16	2817
6-Dec-16	2815
24-Oct-16	2814



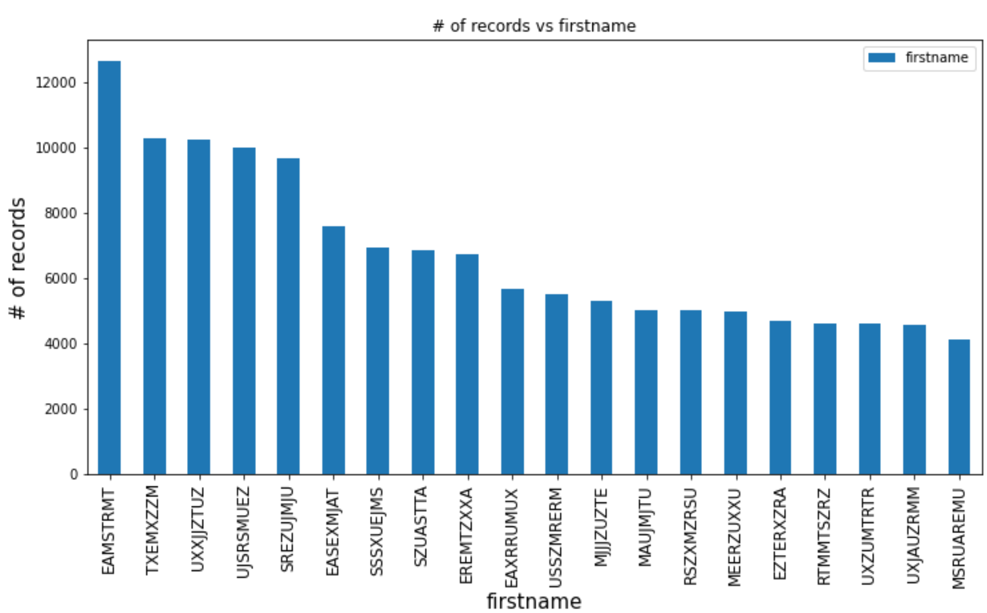
Field 3: SSN

A categorical field listing out the SSN number that each applicant filled in while applying for the product. There are 835,319 unique values for this field and the most common value for SSN is 999-99-9999



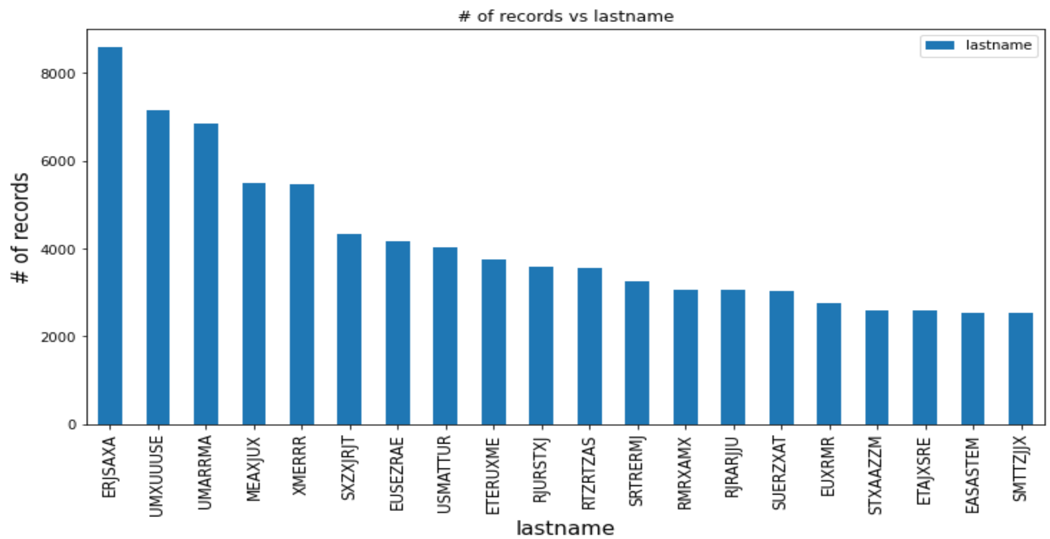
Field 4: First Name

A categorical field which provides the first name of each applicant who has applied for the product. There are 78,136 unique values for this field, and the most common first name in this synthetic data is "Eamstrmt".



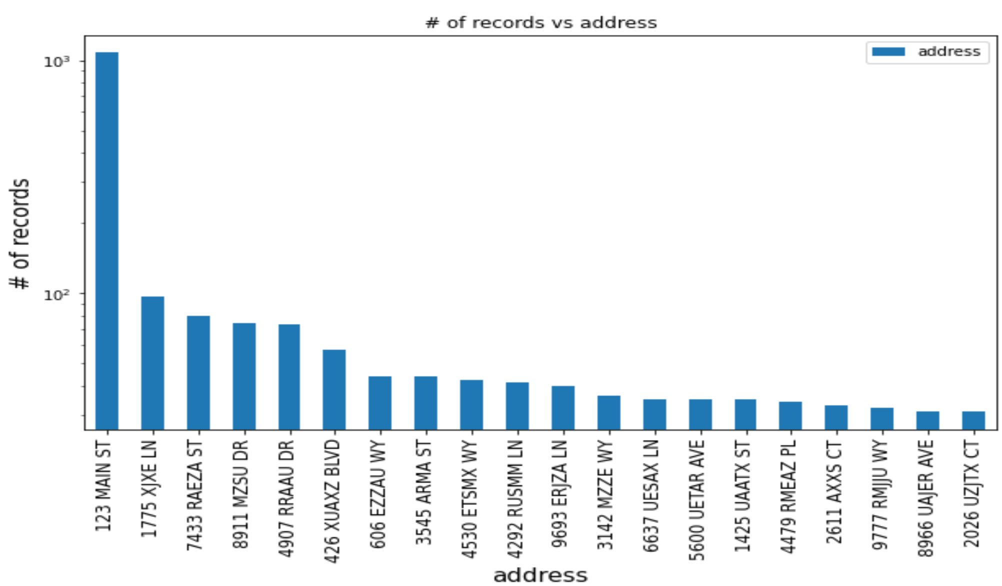
Field 5: Last Name

A categorical field that gives the details of the last name of each applicant who has applied for the product. There are 177,001 unique values in this field, and the most common last name in this synthetic data is "Erjsaxa".



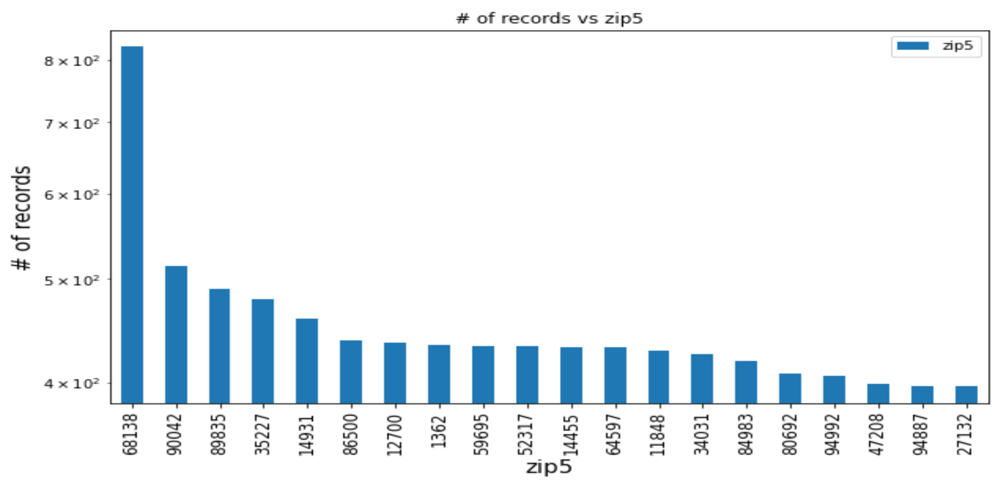
Field 6: Address

A categorical field that gives the address of each applicant who has applied for the product. There are 828,774 unique values for this field, and the most common street address is 1213 Main St.



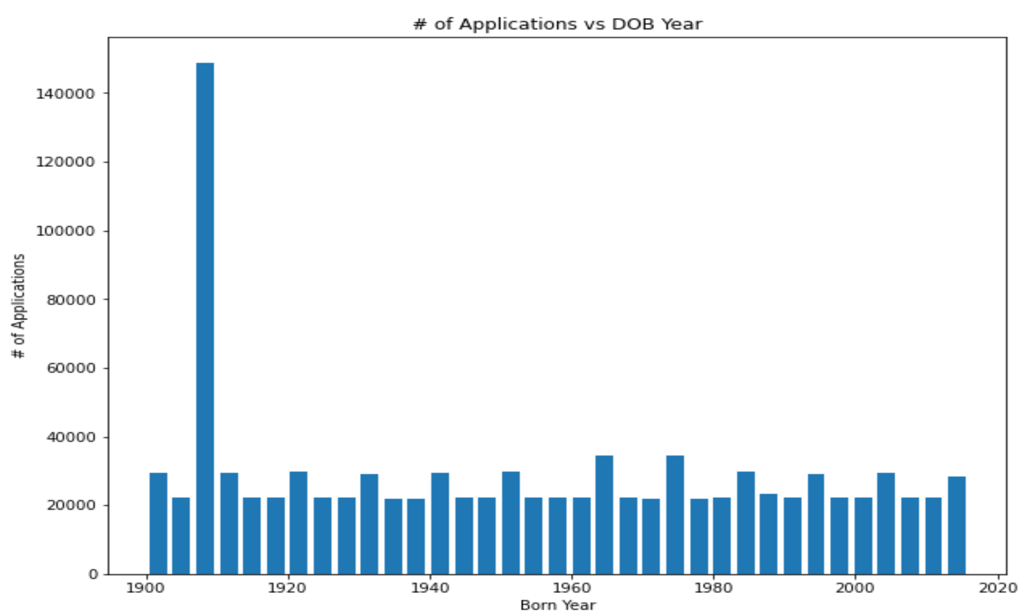
Field 7: ZIP5

A categorical field that lists out the 5 digits of the zip code of the address of each applicant. There are 26,370 unique values in this field, and the most common zip code is 68138.



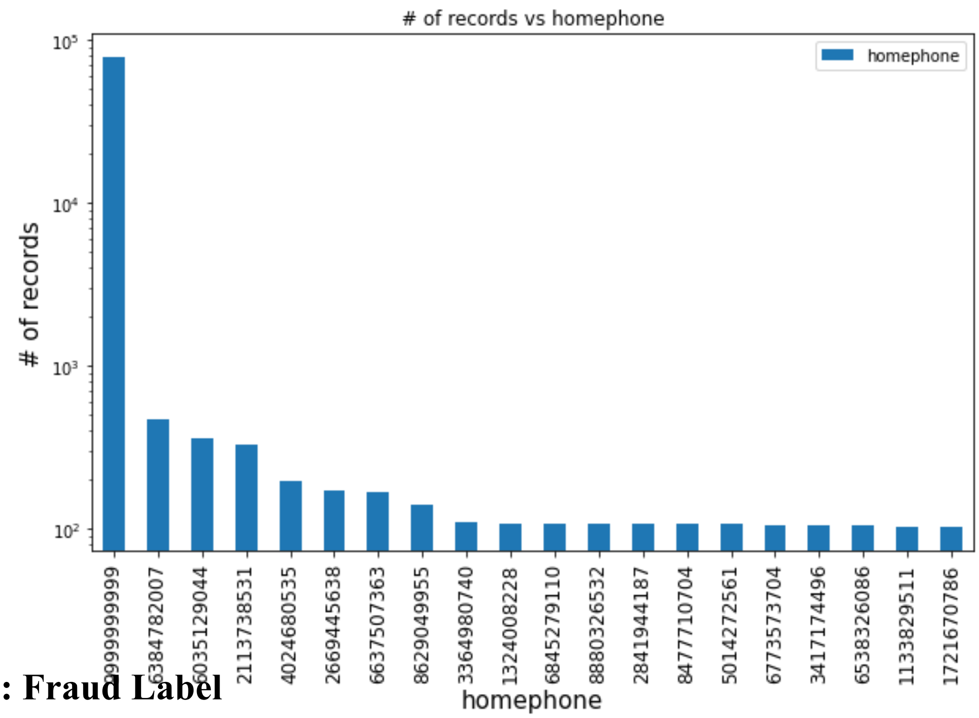
Field 8: Date of Birth (DOB)

A numerical field that gives details of the Date of Birth of each applicant. The most common date of birth for applications is June 26, 1907.



Field 9: Homephone

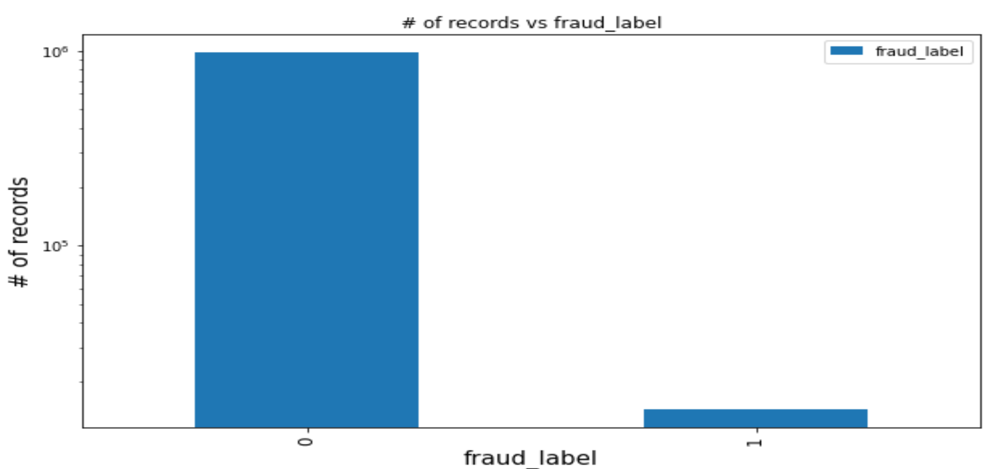
A categorical field that gives details of the home phone number that each applicant has provided while filling out the application for applying for the product. There are 28,244 unique values in this field, and the most common home phone number is 999-999-9999.



Field 10: Fraud Label

A categorical field that classifies and labels each application basis two categories as below:

0: Good Application
- 1: Fraud Applications



APPENDIX B: FULL LIST OF CANDIDATE VARIABLES

record
date
ssn
firstname
lastname
address
zip5
dob
homephone
fraud_label
dow
dow_risk
age
age_group
age_group_risk
name
fulladdress
name_dob
name_fulladdress
name_homephone
fulladdress_dob
fulladdress_homephone
dob_homephone
homephone_name_dob
ssn_firstname
ssn_lastname
ssn_address
ssn_zip5
ssn_dob
ssn_homephone
ssn_name
ssn_fulladdress
ssn_name_dob
ssn_day_since
ssn_count_0

ssn_count_1
ssn_count_3
ssn_count_7
ssn_count_14
ssn_count_30
address_day_since
address_count_0
address_count_1
address_count_3
address_count_7
address_count_14
address_count_30
dob_day_since
dob_count_0
dob_count_1
dob_count_3
dob_count_7
dob_count_14
dob_count_30
homephone_day_since
homephone_count_0
homephone_count_1
homephone_count_3
homephone_count_7
homephone_count_14
homephone_count_30
name_day_since
name_count_0
name_count_1
name_count_3
name_count_7
name_count_14
name_count_30
fulladdress_day_since
fulladdress_count_0
fulladdress_count_1
fulladdress_count_3
fulladdress_count_7

fulladdress_count_14
fulladdress_count_30
name_dob_day_since
name_dob_count_0
name_dob_count_1
name_dob_count_3
name_dob_count_7
name_dob_count_14
name_dob_count_30
name_fulladdress_day_since
name_fulladdress_count_0
name_fulladdress_count_1
name_fulladdress_count_3
name_fulladdress_count_7
name_fulladdress_count_14
name_fulladdress_count_30
name_homephone_day_since
name_homephone_count_0
name_homephone_count_1
name_homephone_count_3
name_homephone_count_7
name_homephone_count_14
name_homephone_count_30
fulladdress_dob_day_since
fulladdress_dob_count_0
fulladdress_dob_count_1
fulladdress_dob_count_3
fulladdress_dob_count_7
fulladdress_dob_count_14
fulladdress_dob_count_30
fulladdress_homephone_day_since
fulladdress_homephone_count_0
fulladdress_homephone_count_1
fulladdress_homephone_count_3
fulladdress_homephone_count_7
fulladdress_homephone_count_14
fulladdress_homephone_count_30
dob_homephone_day_since

dob_homephone_count_0
dob_homephone_count_1
dob_homephone_count_3
dob_homephone_count_7
dob_homephone_count_14
dob_homephone_count_30
homephone_name_dob_day_since
homephone_name_dob_count_0
homephone_name_dob_count_1
homephone_name_dob_count_3
homephone_name_dob_count_7
homephone_name_dob_count_14
homephone_name_dob_count_30
ssn_firstname_day_since
ssn_firstname_count_0
ssn_firstname_count_1
ssn_firstname_count_3
ssn_firstname_count_7
ssn_firstname_count_14
ssn_firstname_count_30
ssn_lastname_day_since
ssn_lastname_count_0
ssn_lastname_count_1
ssn_lastname_count_3
ssn_lastname_count_7
ssn_lastname_count_14
ssn_lastname_count_30
ssn_address_day_since
ssn_address_count_0
ssn_address_count_1
ssn_address_count_3
ssn_address_count_7
ssn_address_count_14
ssn_address_count_30
ssn_zip5_day_since
ssn_zip5_count_0
ssn_zip5_count_1
ssn_zip5_count_3

ssn_zip5_count_7
ssn_zip5_count_14
ssn_zip5_count_30
ssn_dob_day_since
ssn_dob_count_0
ssn_dob_count_1
ssn_dob_count_3
ssn_dob_count_7
ssn_dob_count_14
ssn_dob_count_30
ssn_homephone_day_since
ssn_homephone_count_0
ssn_homephone_count_1
ssn_homephone_count_3
ssn_homephone_count_7
ssn_homephone_count_14
ssn_homephone_count_30
ssn_name_day_since
ssn_name_count_0
ssn_name_count_1
ssn_name_count_3
ssn_name_count_7
ssn_name_count_14
ssn_name_count_30
ssn_fulladdress_day_since
ssn_fulladdress_count_0
ssn_fulladdress_count_1
ssn_fulladdress_count_3
ssn_fulladdress_count_7
ssn_fulladdress_count_14
ssn_fulladdress_count_30
ssn_name_dob_day_since
ssn_name_dob_count_0
ssn_name_dob_count_1
ssn_name_dob_count_3
ssn_name_dob_count_7
ssn_name_dob_count_14
ssn_name_dob_count_30

ssn_count_0_by_3
ssn_count_0_by_7
ssn_count_0_by_14
ssn_count_0_by_30
ssn_count_1_by_3
ssn_count_1_by_7
ssn_count_1_by_14
ssn_count_1_by_30
address_count_0_by_3
address_count_0_by_7
address_count_0_by_14
address_count_0_by_30
address_count_1_by_3
address_count_1_by_7
address_count_1_by_14
address_count_1_by_30
dob_count_0_by_3
dob_count_0_by_7
dob_count_0_by_14
dob_count_0_by_30
dob_count_1_by_3
dob_count_1_by_7
dob_count_1_by_14
dob_count_1_by_30
homephone_count_0_by_3
homephone_count_0_by_7
homephone_count_0_by_14
homephone_count_0_by_30
homephone_count_1_by_3
homephone_count_1_by_7
homephone_count_1_by_14
homephone_count_1_by_30
name_count_0_by_3
name_count_0_by_7
name_count_0_by_14
name_count_0_by_30
name_count_1_by_3
name_count_1_by_7

name_count_1_by_14
name_count_1_by_30
fulladdress_count_0_by_3
fulladdress_count_0_by_7
fulladdress_count_0_by_14
fulladdress_count_0_by_30
fulladdress_count_1_by_3
fulladdress_count_1_by_7
fulladdress_count_1_by_14
fulladdress_count_1_by_30
name_dob_count_0_by_3
name_dob_count_0_by_7
name_dob_count_0_by_14
name_dob_count_0_by_30
name_dob_count_1_by_3
name_dob_count_1_by_7
name_dob_count_1_by_14
name_dob_count_1_by_30
name_fulladdress_count_0_by_3
name_fulladdress_count_0_by_7
name_fulladdress_count_0_by_14
name_fulladdress_count_0_by_30
name_fulladdress_count_1_by_3
name_fulladdress_count_1_by_7
name_fulladdress_count_1_by_14
name_fulladdress_count_1_by_30
name_homephone_count_0_by_3
name_homephone_count_0_by_7
name_homephone_count_0_by_14
name_homephone_count_0_by_30
name_homephone_count_1_by_3
name_homephone_count_1_by_7
name_homephone_count_1_by_14
name_homephone_count_1_by_30
fulladdress_dob_count_0_by_3
fulladdress_dob_count_0_by_7
fulladdress_dob_count_0_by_14
fulladdress_dob_count_0_by_30

fulladdress_dob_count_1_by_3
fulladdress_dob_count_1_by_7
fulladdress_dob_count_1_by_14
fulladdress_dob_count_1_by_30
fulladdress_homephone_count_0_by_3
fulladdress_homephone_count_0_by_7
fulladdress_homephone_count_0_by_14
fulladdress_homephone_count_0_by_30
fulladdress_homephone_count_1_by_3
fulladdress_homephone_count_1_by_7
fulladdress_homephone_count_1_by_14
fulladdress_homephone_count_1_by_30
dob_homephone_count_0_by_3
dob_homephone_count_0_by_7
dob_homephone_count_0_by_14
dob_homephone_count_0_by_30
dob_homephone_count_1_by_3
dob_homephone_count_1_by_7
dob_homephone_count_1_by_14
dob_homephone_count_1_by_30
homephone_name_dob_count_0_by_3
homephone_name_dob_count_0_by_7
homephone_name_dob_count_0_by_14
homephone_name_dob_count_0_by_30
homephone_name_dob_count_1_by_3
homephone_name_dob_count_1_by_7
homephone_name_dob_count_1_by_14
homephone_name_dob_count_1_by_30
ssn_firstname_count_0_by_3
ssn_firstname_count_0_by_7
ssn_firstname_count_0_by_14
ssn_firstname_count_0_by_30
ssn_firstname_count_1_by_3
ssn_firstname_count_1_by_7
ssn_firstname_count_1_by_14
ssn_firstname_count_1_by_30
ssn_lastname_count_0_by_3
ssn_lastname_count_0_by_7

ssn_lastname_count_0_by_14
ssn_lastname_count_0_by_30
ssn_lastname_count_1_by_3
ssn_lastname_count_1_by_7
ssn_lastname_count_1_by_14
ssn_lastname_count_1_by_30
ssn_address_count_0_by_3
ssn_address_count_0_by_7
ssn_address_count_0_by_14
ssn_address_count_0_by_30
ssn_address_count_1_by_3
ssn_address_count_1_by_7
ssn_address_count_1_by_14
ssn_address_count_1_by_30
ssn_zip5_count_0_by_3
ssn_zip5_count_0_by_7
ssn_zip5_count_0_by_14
ssn_zip5_count_0_by_30
ssn_zip5_count_1_by_3
ssn_zip5_count_1_by_7
ssn_zip5_count_1_by_14
ssn_zip5_count_1_by_30
ssn_dob_count_0_by_3
ssn_dob_count_0_by_7
ssn_dob_count_0_by_14
ssn_dob_count_0_by_30
ssn_dob_count_1_by_3
ssn_dob_count_1_by_7
ssn_dob_count_1_by_14
ssn_dob_count_1_by_30
ssn_homephone_count_0_by_3
ssn_homephone_count_0_by_7
ssn_homephone_count_0_by_14
ssn_homephone_count_0_by_30
ssn_homephone_count_1_by_3
ssn_homephone_count_1_by_7
ssn_homephone_count_1_by_14
ssn_homephone_count_1_by_30

ssn_name_count_0_by_3
ssn_name_count_0_by_7
ssn_name_count_0_by_14
ssn_name_count_0_by_30
ssn_name_count_1_by_3
ssn_name_count_1_by_7
ssn_name_count_1_by_14
ssn_name_count_1_by_30
ssn_fulladdress_count_0_by_3
ssn_fulladdress_count_0_by_7
ssn_fulladdress_count_0_by_14
ssn_fulladdress_count_0_by_30
ssn_fulladdress_count_1_by_3
ssn_fulladdress_count_1_by_7
ssn_fulladdress_count_1_by_14
ssn_fulladdress_count_1_by_30
ssn_name_dob_count_0_by_3
ssn_name_dob_count_0_by_7
ssn_name_dob_count_0_by_14
ssn_name_dob_count_0_by_30
ssn_name_dob_count_1_by_3
ssn_name_dob_count_1_by_7
ssn_name_dob_count_1_by_14
ssn_name_dob_count_1_by_30
ssn_unique_count_for_fulladdress_1
ssn_unique_count_for_fulladdress_3
ssn_unique_count_for_fulladdress_7
ssn_unique_count_for_fulladdress_14
ssn_unique_count_for_fulladdress_30
ssn_unique_count_for_fulladdress_60
ssn_unique_count_for_name_dob_1
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ssn_unique_count_for_name_dob_7
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ssn_unique_count_for_name_dob_60
ssn_unique_count_for_name_fulladdress_1
ssn_unique_count_for_name_fulladdress_3

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ssn_unique_count_for_name_fulladdress_60
ssn_unique_count_for_fulladdress_dob_1
ssn_unique_count_for_fulladdress_dob_3
ssn_unique_count_for_fulladdress_dob_7
ssn_unique_count_for_fulladdress_dob_14
ssn_unique_count_for_fulladdress_dob_30
ssn_unique_count_for_fulladdress_dob_60
ssn_unique_count_for_dob_homephone_1
ssn_unique_count_for_dob_homephone_3
ssn_unique_count_for_dob_homephone_7
ssn_unique_count_for_dob_homephone_14
ssn_unique_count_for_dob_homephone_30
ssn_unique_count_for_dob_homephone_60
ssn_unique_count_for_ssn_lastname_1
ssn_unique_count_for_ssn_lastname_3
ssn_unique_count_for_ssn_lastname_7
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ssn_unique_count_for_ssn_lastname_30
ssn_unique_count_for_ssn_lastname_60
ssn_unique_count_for_ssn_zip5_1
ssn_unique_count_for_ssn_zip5_3
ssn_unique_count_for_ssn_zip5_7
ssn_unique_count_for_ssn_zip5_14
ssn_unique_count_for_ssn_zip5_30
ssn_unique_count_for_ssn_zip5_60
ssn_unique_count_for_ssn_homephone_1
ssn_unique_count_for_ssn_homephone_3
ssn_unique_count_for_ssn_homephone_7
ssn_unique_count_for_ssn_homephone_14
ssn_unique_count_for_ssn_homephone_30
ssn_unique_count_for_ssn_homephone_60
ssn_unique_count_for_ssn_name_1
ssn_unique_count_for_ssn_name_3
ssn_unique_count_for_ssn_name_7
ssn_unique_count_for_ssn_name_14

ssn_unique_count_for_ssn_name_30
ssn_unique_count_for_ssn_name_60
ssn_unique_count_for_ssn_fulladdress_1
ssn_unique_count_for_ssn_fulladdress_3
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ssn_unique_count_for_ssn_name_dob_60
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dob_homephone_unique_count_for_ssn_lastname_3
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dob_homephone_unique_count_for_ssn_lastname_60
dob_homephone_unique_count_for_ssn_zip5_1
dob_homephone_unique_count_for_ssn_zip5_3
dob_homephone_unique_count_for_ssn_zip5_7
dob_homephone_unique_count_for_ssn_zip5_14
dob_homephone_unique_count_for_ssn_zip5_30
dob_homephone_unique_count_for_ssn_zip5_60
dob_homephone_unique_count_for_ssn_homephone_1
dob_homephone_unique_count_for_ssn_homephone_3
dob_homephone_unique_count_for_ssn_homephone_7
dob_homephone_unique_count_for_ssn_homephone_14
dob_homephone_unique_count_for_ssn_homephone_30
dob_homephone_unique_count_for_ssn_homephone_60
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dob_homephone_unique_count_for_ssn_name_dob_14

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ssn_lastname_unique_count_for_ssn_1
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ssn_name_dob_unique_count_for_ssn_zip5_1
ssn_name_dob_unique_count_for_ssn_zip5_3
ssn_name_dob_unique_count_for_ssn_zip5_7
ssn_name_dob_unique_count_for_ssn_zip5_14
ssn_name_dob_unique_count_for_ssn_zip5_30
ssn_name_dob_unique_count_for_ssn_zip5_60

ssn_name_dob_unique_count_for_ssn_homephone_1
ssn_name_dob_unique_count_for_ssn_homephone_3
ssn_name_dob_unique_count_for_ssn_homephone_7
ssn_name_dob_unique_count_for_ssn_homephone_14
ssn_name_dob_unique_count_for_ssn_homephone_30
ssn_name_dob_unique_count_for_ssn_homephone_60
ssn_name_dob_unique_count_for_ssn_name_1
ssn_name_dob_unique_count_for_ssn_name_3
ssn_name_dob_unique_count_for_ssn_name_7
ssn_name_dob_unique_count_for_ssn_name_14
ssn_name_dob_unique_count_for_ssn_name_30
ssn_name_dob_unique_count_for_ssn_name_60
ssn_name_dob_unique_count_for_ssn_fulladdress_1
ssn_name_dob_unique_count_for_ssn_fulladdress_3
ssn_name_dob_unique_count_for_ssn_fulladdress_7
ssn_name_dob_unique_count_for_ssn_fulladdress_14
ssn_name_dob_unique_count_for_ssn_fulladdress_30
ssn_name_dob_unique_count_for_ssn_fulladdress_60