Detecting Fraud in the NY Property Dataset

DSO 562 Project 1 Report

Team 4

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Glossary

Executive Summary

This report provides an analysis and evaluation of The City of New York Property Valuation and Assessment Data for detecting fraud using unsupervised machine learning methods. The tools used are R and Tableau, and methods for analysis include Principal Component Analysis and Autoencoder.

The original data set contains records of more than 1 million properties across the city of New York and information on their sizes, values, owner, building classes, tax classes, etc. The general process of analysis follows data cleaning, building expert variables, standardization and dimensionality reduction, applying fraud algorithm, calculating fraud score, and identifying potential fraud.

Using heuristic fraud algorithm and Autoencoder, a fraud score is calculated for each of the one million properties. Records with high scores are determined to be potentially fraudulent. The report further finds the high score records of two unsupervised machine learning methods partially overlapped, and determines that the overlapped part of the top records from both methods are very likely to be fraudulent.

Detailed examination of the most suspicious records indicates that potentially fraudulent properties have significantly higher values in a lot of variables compared to the majority of records. Some properties are also significantly undervalued and hence paying lower taxes than they should. Meanwhile, most of the potentially fraudulent properties are located in Manhattan borough and belong to the tax class 4. Further examination of the top 10 most suspicious records shows that the owners of these properties are mostly real estate agencies and organizations instead of single households.

Part I. Data Overview

The City of New York Property Valuation and Assessment Data file is a public available dataset posted by the Department of Finance on the City of New York Open Data website. The dataset contains records of more than 1 million properties across the city of New York and information on their sizes, values, owner, building classes, tax classes, etc. The dataset contains a total of 1,048,575 records (rows) and 30 variables (columns). Among the 30 variables, there are 13 categorical variables, 14 numeric variables, 2 text variables, and 1 date variable. All of the records are taken from November 2011.

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

Variable Name: **RECORD**

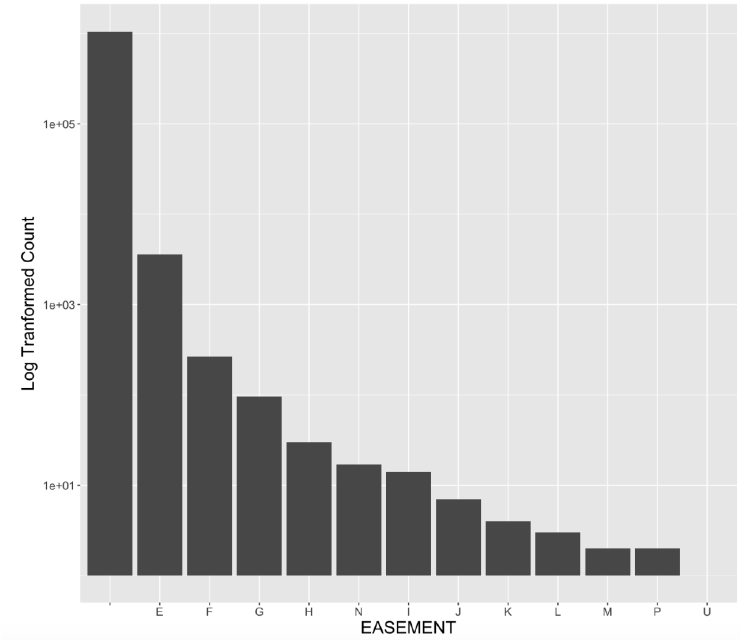
RECORD is a categorical variable. It works as the ordinal reference number for each property Record. It has 1,048,575 unique values, ranging from 1 to 1,048,575. No repeated values or missing values exist.

Variable Name: **BBLE**

BBLE is a nominal categorical variable with 10 or 11 digits. It is the concatenation of BORO code (1 digit), BLOCK code (5 digit), LOT code (4 digit) and EASEMENT code (1 digit if exists). It has 1,048,575 unique values, with no repeated or missing values.

Variable Name: **EASEMENT**

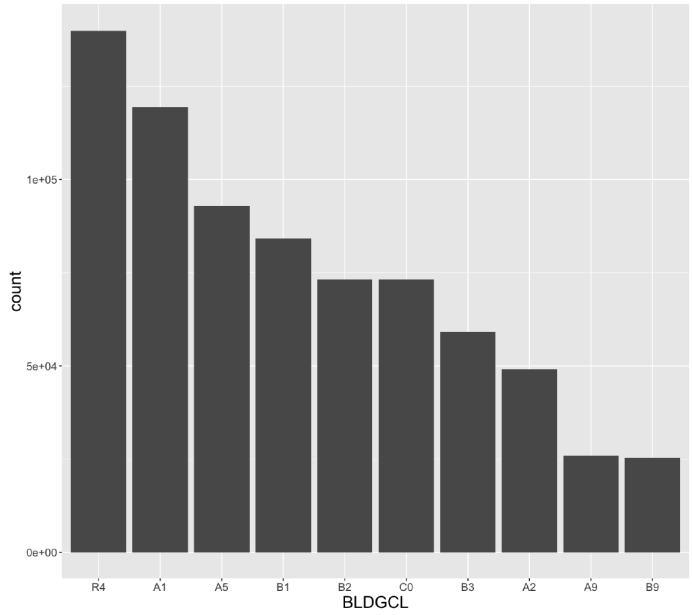
EASEMENT is a nominal categorical variable representing the property's easement type. It has 13 levels – "", "E", "F", "G", "H", "I", "J", "K", "L", "M", "N", "P", "U". The null value indicates the property does not have any special easement type. No missing values exist. The sorted bar chart with log transformed y axis is shown below:



Level	Counts
	1044532 (99.6%)
E	3603
F	265
G	95
H	30
I	14
J	7
K	4
L	3
M	2
N	17
P	2
U	1

Variable Name: **BLDGCL**

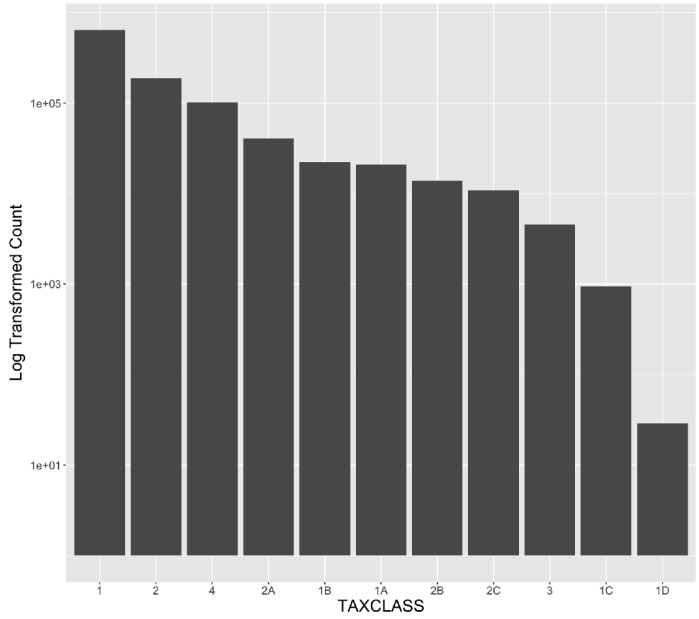
BLDGCL is a nominal categorical variable indicating the building class. It has 200 unique levels. Each level has 2 digits – the first digit is a character from A to Z, the second digit is a number from 0 to 9. No missing values exist. The top 10 most frequently occurred BLDGCL is shown below:



BLDGCL	Percentage(%)
R4	13.3
A1	11.4
A5	8.9
B1	8
B2	7
C0	8
B3	5.6
A2	4.7
A9	2.5
B9	2.4

Variable Name: **TAXCLASS**

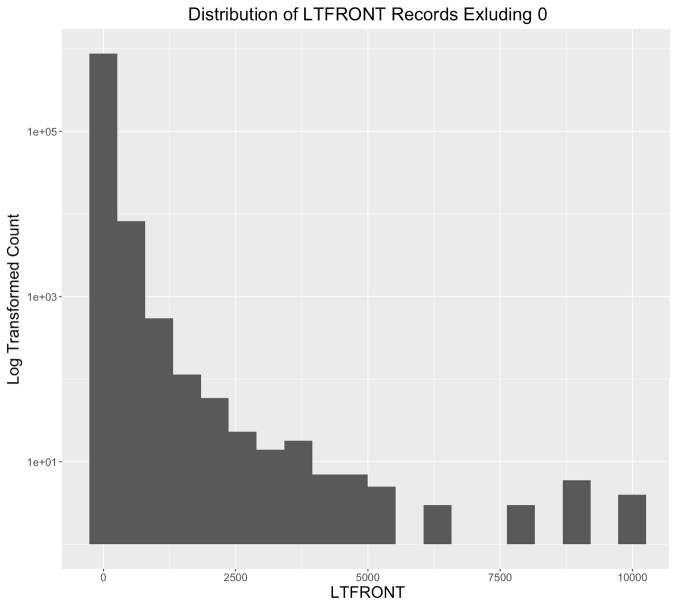
TAXCLASS is a categorical variable indicating the tax class of the property. It has 11 unique levels – “1”, “1A”, “1B”, “1C”, “1D”, “2”, “2A”, “2B”, “2C”, “3”, and “4”. No missing values exist. Sorted TAXCLASS levels are shown below:



Level	Percentage(%)
1	61.4
2	18.0
4	9.8
2A	3.9
1B	2.1
1A	2.0
2B	1.3
2C	1.0
3	0.4
1C	0.1
1D	0.0

Variable Name: **LTFRONT**

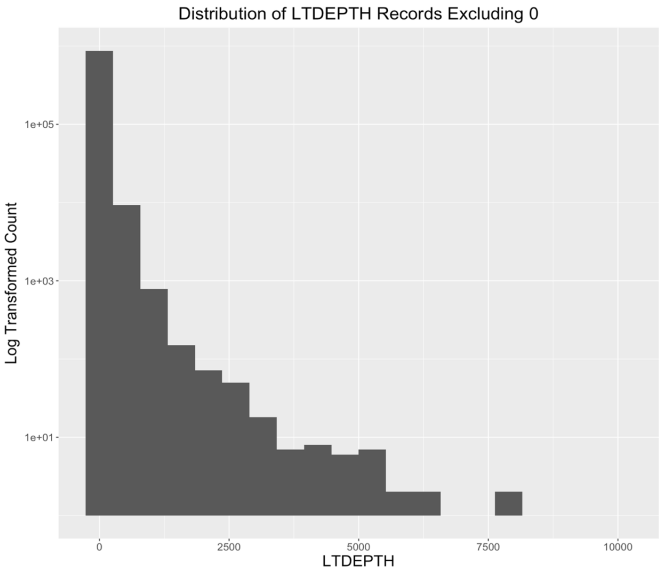
LTFRONT is a numeric variable representing the length of lot frontage in feet. It has 1277 unique values ranging from 0 to 9999. No missing values exist. There are 168,867 records of 0 LTFRONT. A LTFRONT of 0 may indicate missing value. The statistics and distribution excluding 0 records are shown below:



Minimum	1
Maximum	9999
Median	25
Mean	43.12
Mode	20
SD	78.62

Variable Name: **LTDEPTH**

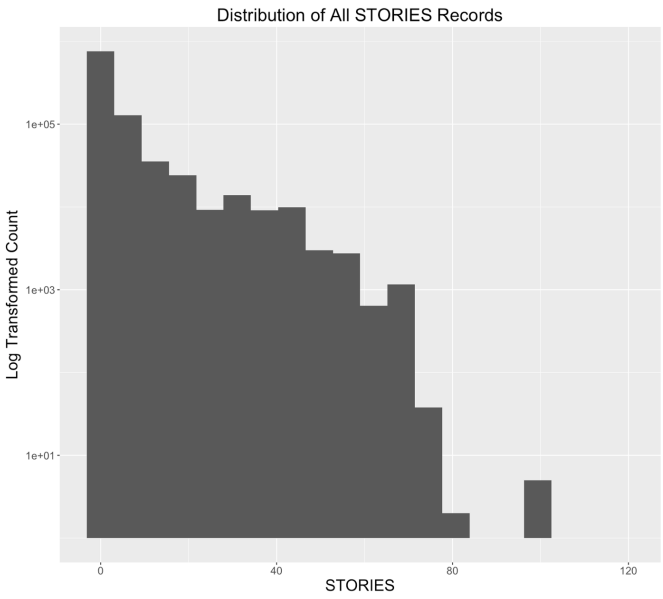
LTDEPTH is a numeric variable representing the length of lot depth in feet. It has 1336 unique values ranging from 0 to 9999. No missing values exist. There are 169,888 records of 0 LTDEPTH, and a LTDEPTH of 0 may indicate missing value. The statistics and distribution excluding 0 records are shown below:



Minimum	1
Maximum	9999
Median	100
Mean	105.34
Mode	100
SD	70.71

Variable Name: **STORIES**

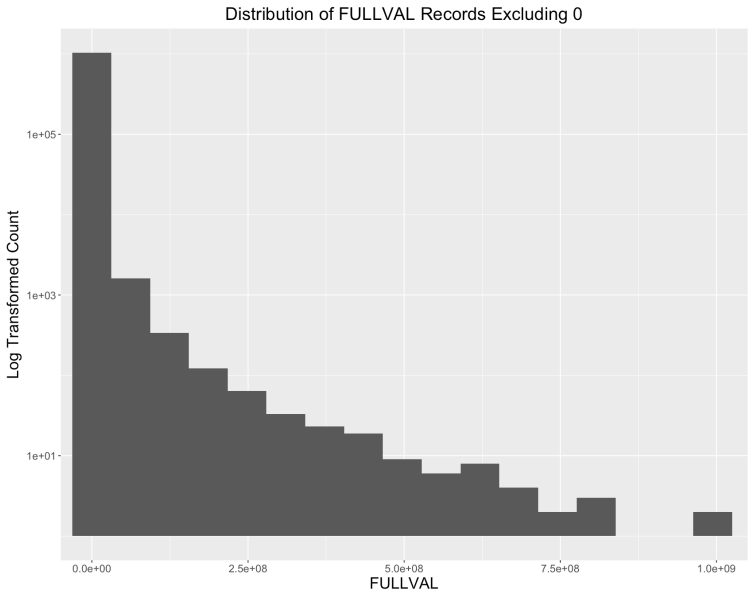
STORIES is a numeric variable representing the number of stories of the property. It has 112 unique values ranging from 1 to 119. There are 52,142 missing values in the STORIES field. The statistics and distribution are shown below:



Minimum	1
Maximum	119
Median	2
Mean	5.06
Mode	2
SD	8.43

Variable Name: **FULLVAL**

FULLVAL is a numeric variable representing the full value of the property. It has 108277 unique values ranging from 0 to about 6,000,000,000. There are 12,762 properties with the FULLVAL of 0 in the dataset. No missing values exist. The statistics and distribution are shown below:

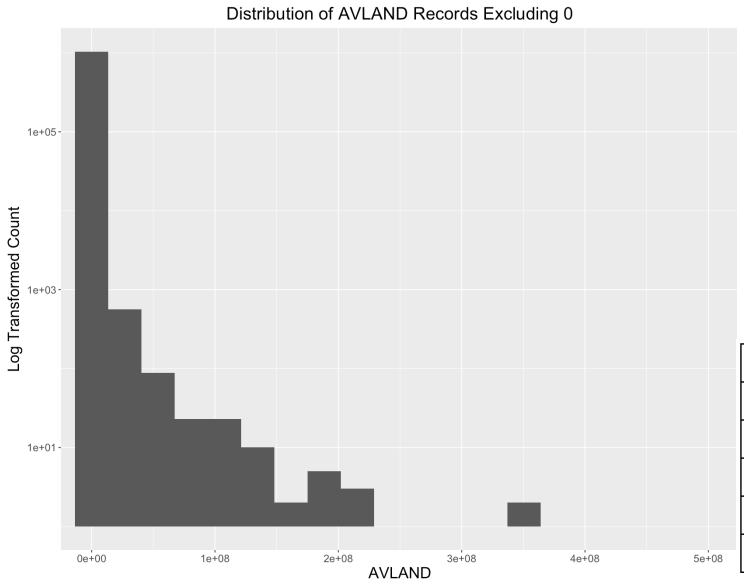


Minimum	4
Maximum	6.15E+09
Median	45000
Mean	8.91E+05
Mode	502000
SD	1.17E+07

Variable Name: **AVLAND**

AVLAND is a numeric variable representing the assessed value of the land. It has 70,529 unique values ranging from 0 to about 2,700,000,000. There are 12,764 properties with the

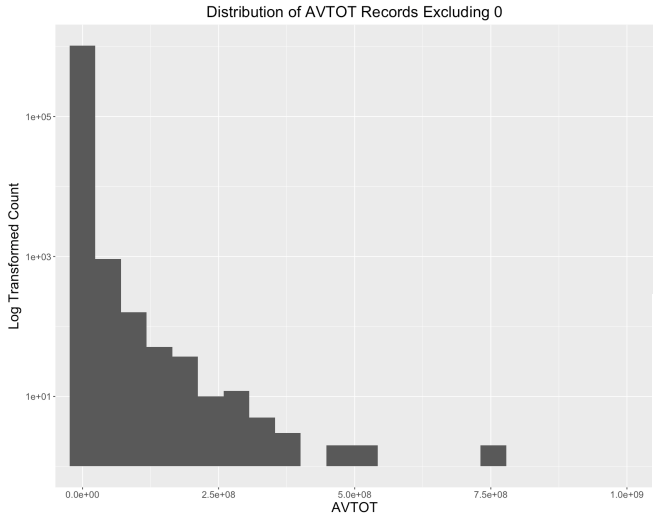
AVLAND of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown below:



Minimum	1
Maximum	2.67E+09
Median	13751
Mean	86054.72
Mode	45000
SD	4.10E+06

Variable Name: **AVTOT**

AVTOT is a numeric variable representing the assessed total value of the property. It has 112294 unique values ranging from 0 to about 4,700,000,000. There are 12,762 properties with the AVTOT of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown below:

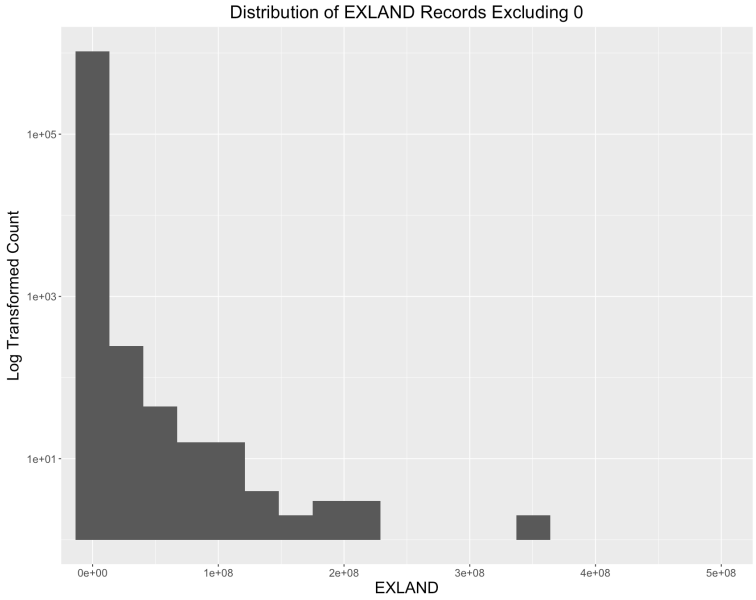


Minimum	1
Maximum	4.67E+09
Median	25560
Mean	233601.3
Mode	16588
SD	6.99E+06

Variable Name: **EXLAND**

EXLAND is a numeric variable representing the value of the exempt land. The value of EXLAND

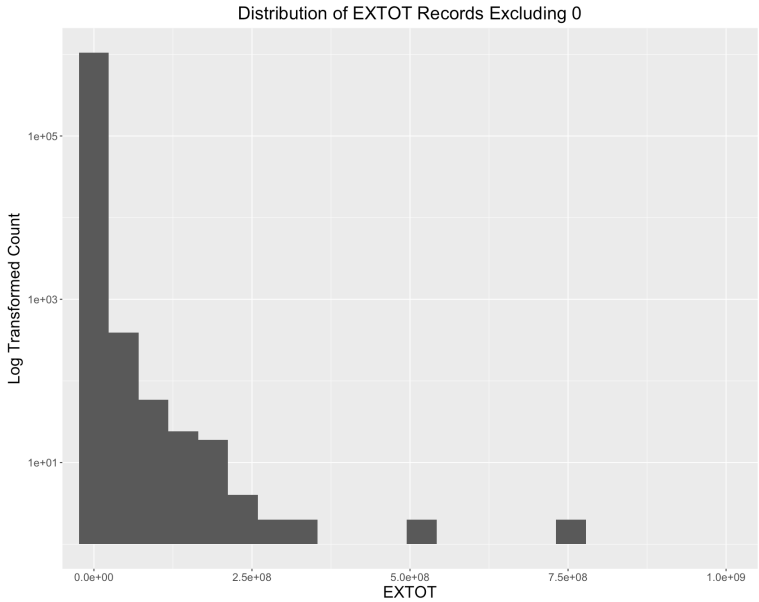
is always smaller or equal to AVLAND. EXLAND has 33186 unique values ranging from 0 to about 2,700,000,000. There are 484,224 properties with the EXLAND of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown as below:



Minimum	1
Maximum	2.67E+09
Median	1620
Mean	68397.01
Mode	1620
SD	5485336

Variable Name: **EXTOT**

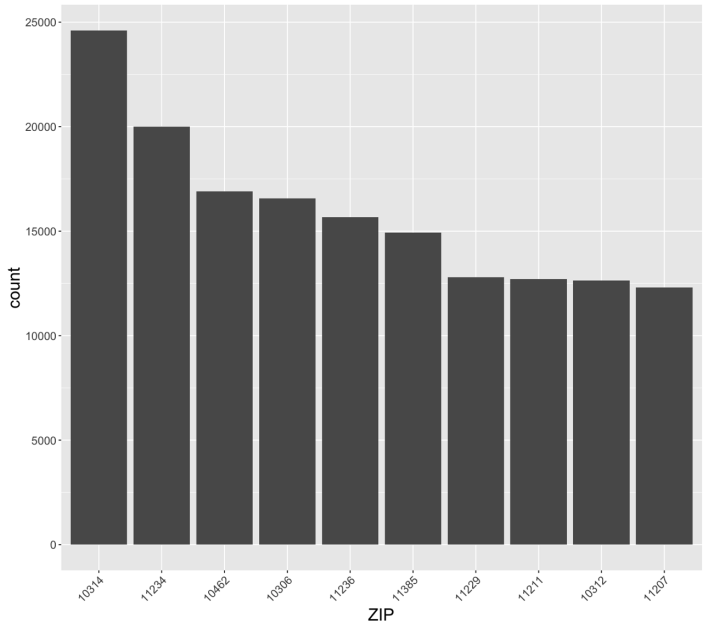
EXTOT is a numeric variable representing the total value of the exempt property. The value of EXTOT is always smaller or equal to AVTOT. EXTOT has 63805 unique values ranging from 0 to about 4,700,000,000. There are 425,999 properties with the EXTOT of 0 in the dataset. No missing values exist. . The statistics and distribution excluding 0 records are shown below:



Minimum	1
Maximum	4.67E+09
Median	1620
Mean	155867.1
Mode	1620
SD	8536636

Variable Name: **ZIP**

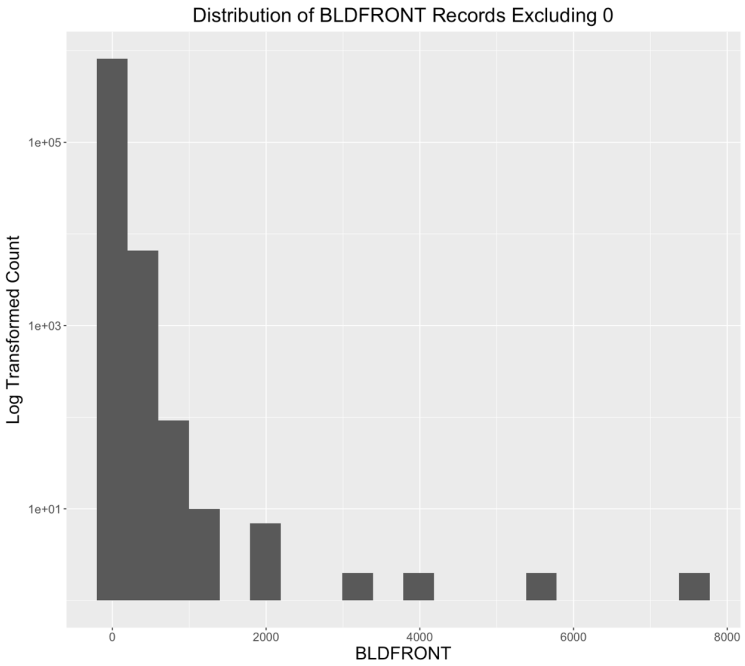
ZIP is a categorical variable, recording the zipcode of the property. ZIP has 197 unique values and 26,356 missing values. There are three obvious anomalous records with ZIP of 33803, which should be in Florida. The top 20 most frequently occurred ZIP values are:



ZIP	Percentage(%)
10314	2.3
11234	1.9
10462	1.6
10306	1.6
11236	1.5
11385	1.4
11229	1.2
11211	1.2
10312	1.2
11207	1.2

Variable Name: **BLDFRONT**

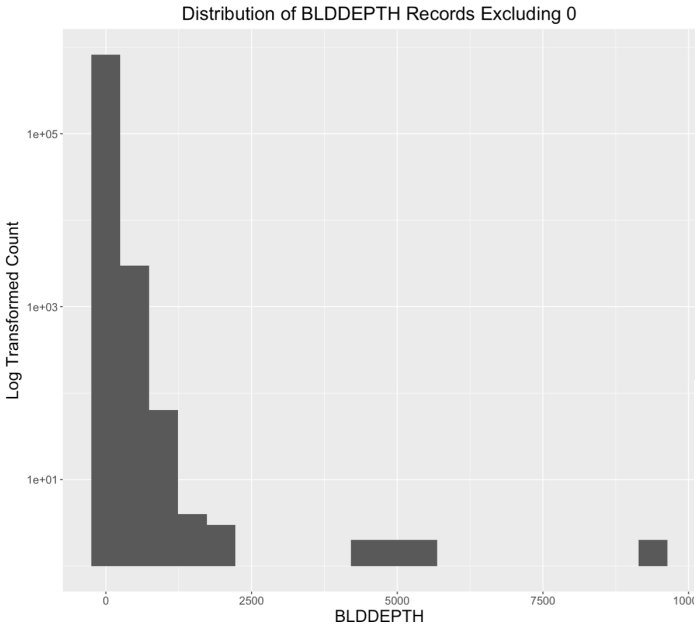
BLDFRONT is a numeric variable representing the length of building frontage in feet. It has 610 unique values ranging from 0 to 7575. No missing values exist. However, there are 224,661 records with value 0, which could be in fact missing values. The statistics and distribution excluding all records with 0 BLDFRONT are shown below:



Minimum	1
Maximum	7575
Median	20
Mean	29.29
Mode	20
SD	38.03

Variable Name: **BLDDEPTH**

BLDDEPTH is a numeric variable representing the length of building depth in feet. It has 620 unique values ranging from 0 to 9393. No missing values exist. However, there are 224,699 records with value 0, which could be in fact missing values. The statistics and distribution excluding all records with 0 BLDFRONT are shown below:



Minimum	1
Maximum	9393
Median	44
Mean	51.00
Mode	40
SD	42.42

Part II. Data Cleaning

Before constructing expert variables, we performed data cleaning to prepare the dataset for subsequent analysis.

1. Adjusting and combining existing variables

For the variables **BBLE**, we extracted its first digit and changed the variable name to "**BORO**", indicating the borough where the property located.

For the variable **BLDGCL**, since there used to be 200 unique levels in the form of "[A-Z][0-9]", and some of the categories had very few records, we only kept the first digit (the character digit) of the BLDGCL variable. Therefore, there are only 26 unique levels after the transformation.

We defined the product of the variables **LTFRONT** and **LTDEPTH** as a new variable **LOT_AREA**, indicating the lot size of each property.

We multiplied the values of **BLDFRONT**, **BLDDEPTH** and **STORIES**, and defined the output as a new variable **BLD_VOLUME**, indicating the volume of each building.

2. Removing variables

We removed three types of variables: less informative variables, less populated variables, and already aggregated variables.

We found 7 less informative variables - **STADDR**, **OWNER**, **BLOCK**, **LOT**, **PERIOD**, **YEAR** and **VALTYPE**. Although the text variables **STADDR** and **OWNER** included important identification information, we regarded them as less informative variables since there are too many levels to feed into our fraud detection model. As for variable **BLOCK** and **LOT**, although they were id numbers for the properties, they were not unique within each **BORO**. Thus they were also determined to be less informative variables. For the variables **PERIOD**, **YEAR** and **VALTYPE**, all of the records took the same value, providing no valuable information to our analysis. During the data cleaning process, we removed all of the above 7 less informative variables.

There are 7 less populated variables **EXCD1**, **EXMPTCL**, **AVLAND2**, **AVTOT2**, **EXLAND2**, **EXTOT2** and **EXCD2**. They could not serve as strong indicators of fraud considering their actual meaning. Therefore, we removed these variables from the dataset. Their percentage populated are shown below.

Variable	% populated
EXCD1	59.4%
EXMPTCL	1.4%
AVLAND2	26.8%
AVTOT2	26.8%
EXLAND2	8.3%
EXTOT2	12.4%
EXCD2	8.7%

Since we created the variable **LOT_AREA** based on **LTFRONT** and **LTDEPTH**, and we created the variable **BLD_VOLUME** based on **BLDFRONT**, **BLDDEPTH** and **STORIES**, we decided to remove **LTFRONT**, **LTDEPTH**, **BLDFRONT**, **BLDDEPTH** and **STORIES** from our dataset.

3. Filling in the missing values

For the variable **EASEMENT**, 99.6% of the properties in this dataset were left blank, indicating they did not have an easement type. Since we considered that **EASEMENT** could be an important indicator for fraud, we filled in the missing values with a newly-created category “NO”.

For the variable **STORIES**, there were 5% records with missing values. We filled in the missing values with the average **STORIES** in their own **TAXCLASS**.

For the variable **ZIP**, there were 2.5% records with missing values. We filled in the missing values with “00000”.

After the data cleaning process, we kept 13 variables in the dataset: **RECORD**, **FULLVAL**, **AVLAND**, **AVTOT**, **EXLAND**, **EXTOT**, **BORO**, **EASEMENT**, **BLDGCL**, **TAXCLASS**, **ZIP**, **LOT_AREA**, **BLD_VOLUME**.

Part III. Variable Construction

To begin with, we divided the original variables into two sets, 9 numerators and 6 denominators, before constructing expert variables.

The 9 numerators variables are:

1. **FULLVAL**: full value of building
2. **AVLAND**: assessed value of land
3. **AVTOT**: assessed value of property
4. **EXLAND**: exemption value of land
5. **EXTOT**: exemption value of property
6. **FULLVAL / AVTOT**: the ratio of full value of building to assessed value of property
7. **AVTOT / EXTOT**: the ratio of assessed value to exemption value of property
8. **AVLAND / EXLAND**: the ratio of assessed value to exemption value of land
9. **FULLVAL / EXTOT**: the ratio of full value of building to exemption value of property

All the numerators are numeric variables, which closely relate to the monetary value of properties. 1-4 were from the original dataset, while 6-9 were created by us to capture the relationship between full values, assessed values, and exemption values.

When calculating those ratios, we encountered many 0s in some of the numerical variables. Our calculation gave back infinity if we calculated their averages and put them in the denominator position. Value 0s themselves could be signs of fraud, while sometimes they could be valid and reasonable as well. For example, 0 in **EXLAND** meant the property did not have exemptions. Therefore, replacing them with the median value might not be reasonable. Our decision was to substitute these 0s with 1s. Since those values were large enough (usually in thousands), 1s would still be small enough for us to detect anomaly without causing calculation problems.

The 6 denominator variables are:

1. **BORO**: borough code
2. **EASEMENT**: easement is a non-possessory right to use and/or enter onto the real property of another without possessing it.
3. **BLDGCL**(1st): building class
4. **TAXCLASS**: tax class
5. **LOT_AREA** =LOTFRONT * LOTDEPTH: measurement of lot area
6. **BLD_VOLUME** = STORIES * BLDP * BLFT: measurement of building volume
7. **ZIP**: zip code

All the denominator variables (except **LOT_AREA** and **BLD_VOLUME**) are used to classify numerators. All the denominator variables are used to classify numerators. That is, we divided all those numerators by these denominator variables, calculated median of numerical variables in each group, and divided numerical variables by the median of each group.

For example, if we used **FULLVAL** (numerator) and **TAXCLASS** (denominator), the expert

variable would be **FULLVAL/ (median of FULLVAL in the TAXCLASS that the property belongs)**.

For denominators **LOT_AREA** and **BLD_VOLUME**, the expert variables were the ratios of the value divided by area (or divided by volume) of a particular property to the average value divided by area (or divided by volume). For example, when we combined **FULLVAL** and **BLD_VOLUME**, we created a variable **FULLVAL/BLD_VOLUME/(median of FULLVAL/BLD_VOLUME)**. Again, we substituted 0s in **BLD_VOLUME** and **LOT_AREA** (both usually in thousands) with 1s to avoid calculation error.

We exploited the combinations of each numerators and denominators, except the combinations **AVLAND** and **BLDGVOL**, **EXLAND** and **BLDGVOL**. The reason was that we believed the value of land was not closely related to the building volume.

In total, we created **61** expert variables.

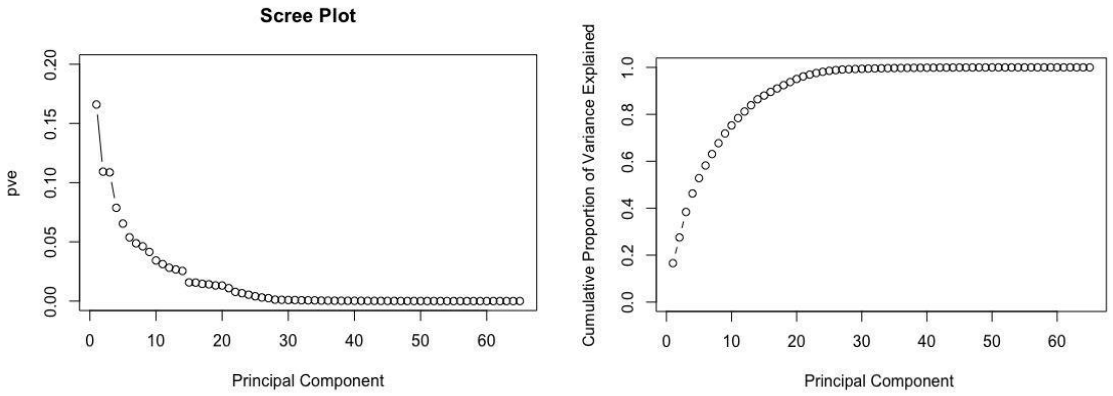
Part IV. Fraud Algorithm

After we had all the expert variables and their respective values at hand, we started the process of standardization and dimensionality reduction for further analysis.

We performed principal components analysis using the **prcomp()** function, which was one of several functions in R that could perform PCA. By default, the **prcomp()** function centers the variables to have mean zero. By using the option **scale = TRUE**, we scaled the variables to have standard deviation of 1. The 'center' and 'scale' components correspond to the means and standard deviations of the variables that were used for standardization prior to implementing PCA.

The **rotation** matrix provided the principal component loadings, each column of **pr.out$rotation** contained the corresponding principal component loading vector.

To compute the proportion of variance explained by each principal component, we simply divided the variance explained by each PC by the total variance explained by all 61 PCs. We made the scree plot and cumulative plot to determine which PCs to keep. We would like to use the smallest number of PCs required to get a good understanding of the data. By examining the scree plot below, we discovered that there is a significant drop between PC14 and PC15. Thus, we decided to keep PC1 through PC14, which explained approximately 90% of the entire dataset.



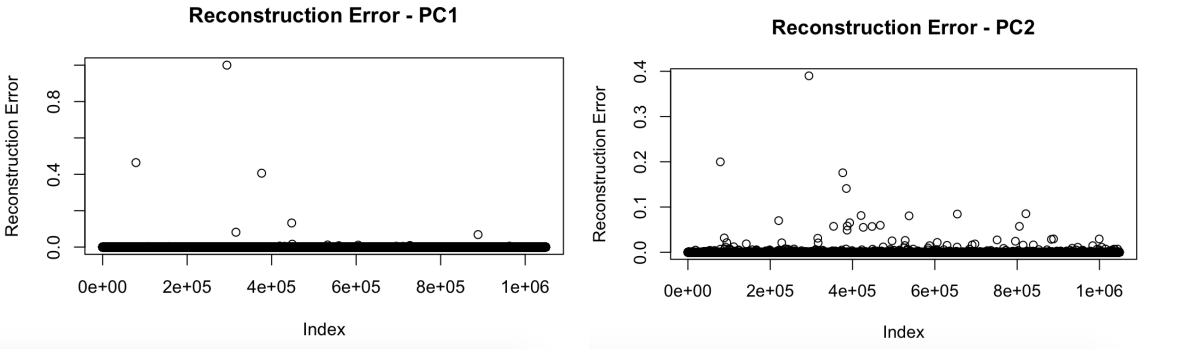
Finally, we reduced the dimension of the original dataset by multiplying the PCA matrix and the original data matrix to get the final dataset for further calculation of the fraud scores.

We used two different ways to calculate fraud scores. The first one being autoencoder, and the second one was a heuristic algorithm.

Autoencoder:

First we tried to autoencode our PCs using an R package called "**h2o**". Then, we called the **deep learning** function with parameter "autoencoder" set to TRUE. This function took the original dataset with all the PCs and autoencoded it. We then called the **h2o.anomaly** function to reconstruct the original dataset using the reduced set of features and calculated a mean squared error between both. We set the "per_feature" parameter to TRUE because we wanted a reconstruction mean error based on individual features. We saved the reconstruction error in a dataset called "**error**".

From plotting of the "**error**" dataset, we could see that there were some abnormal values, which might indicate fraud. Below are examples of the distribution of reconstruction errors for PC1 and PC2:



In the end we summed the reconstruction error values of all the PCs to get a single score, which would be our fraud score from autoencoder, for each of the record.

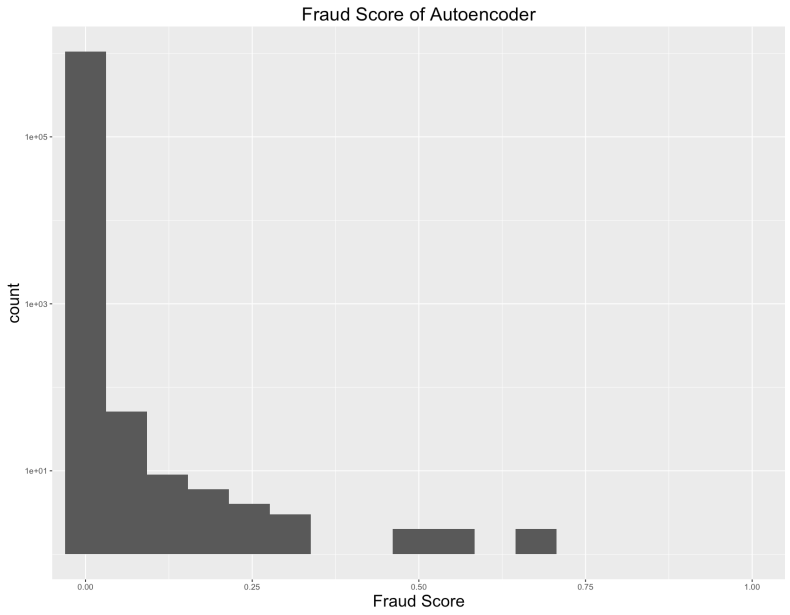
Heuristic Algorithm:

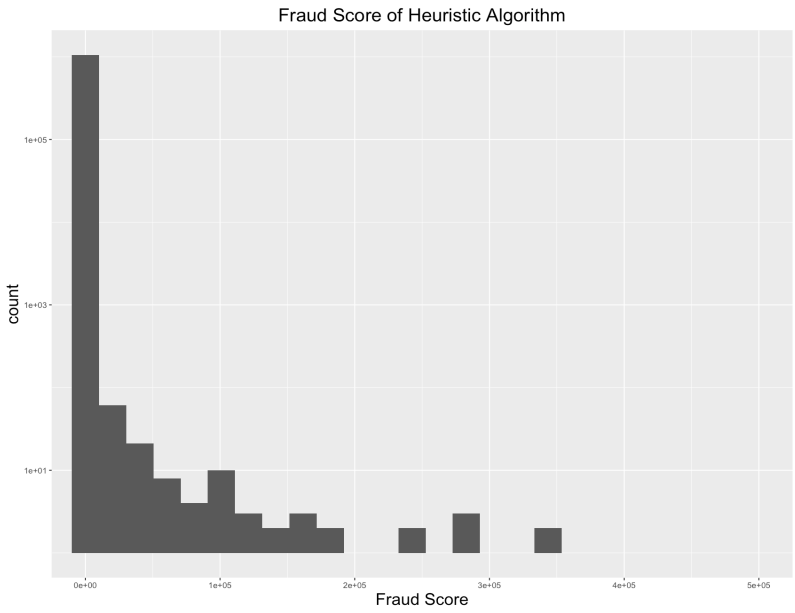
Our algorithm was calculating the **mahalanobis distance** between each record and the (mean,covariance) of records within each particular PC. The **mahalanobis distance** was our fraud score for each record. It was calculated using the function '**mahalanobis**' in R.

Part V. Results

Having fraud scores ready, we sorted the records according to fraud scores from both autoencoder and heuristic algorithm outcomes. Not surprisingly, the majority of records had low fraud scores while a small proportion of the records had typically high fraud scores.

Below is an overview of what the distribution of fraud scores from both methods:





We decided to look at the **overlapping** part of the top **1%** high score records from autoencoder output and the top **1%** high score records from heuristic algorithm output. About **70%** of the records from these two algorithms matched, so we selected these overlapped records as the

best candidates for potential fraud.

General Trends:

We found some general trends on the overlapped part of the top 1% high score records. The following table compares the mean, median and standard deviation of **"Top 1%"** records with the mean, median and standard deviation of complete data.

	Complete Data				Top 1% records			
	number	mean	stdev	median	number	mean	stdev	median
LTFRONT	1048575	36	74	25	7217	221	457	125
LTDEPTH	1048575	88	75	100	7217	238	379	131
STORIES	996433	5	8	2	6754	12	13	6
BLDFRONT	1048575	23	36	20	7217	114	143	92
BLDDEPTH	1048575	40	43	39	7217	121	114	99
LOT_AREA	1048575	5902	154727	2400	7217	153885	1754442	17574
BLD_VOLUME	1048575	19043	2315821	1520	7217	232034	969582	60000
FULLVAL	1048575	880488	11702927	446000	7217	37590715	134865357	12230000
AVLAND	1048575	85995	4100755	13646	7217	6614340	48918875	1413000
AVTOT	1048575	230758	6951206	25339	7217	16935641	81733286	5175000
EXLAND	1048575	36812	4024330	1620	7217	3565607	48339361	0
EXTOT	1048575	92544	6578281	1620	7217	8156874	78753026	0
FV_AT	1048575	22	429	18	7217	40	1587	2
AT_ET	1048575	95286	1942435	17	7217	7532982	22081850	2169000
FV_ET	1048575	348064	4339495	352	7217	17883478	48834099	7310000
AL_EL	1048575	39253	777335	12	7217	3022125	8811510	607500

Insights:

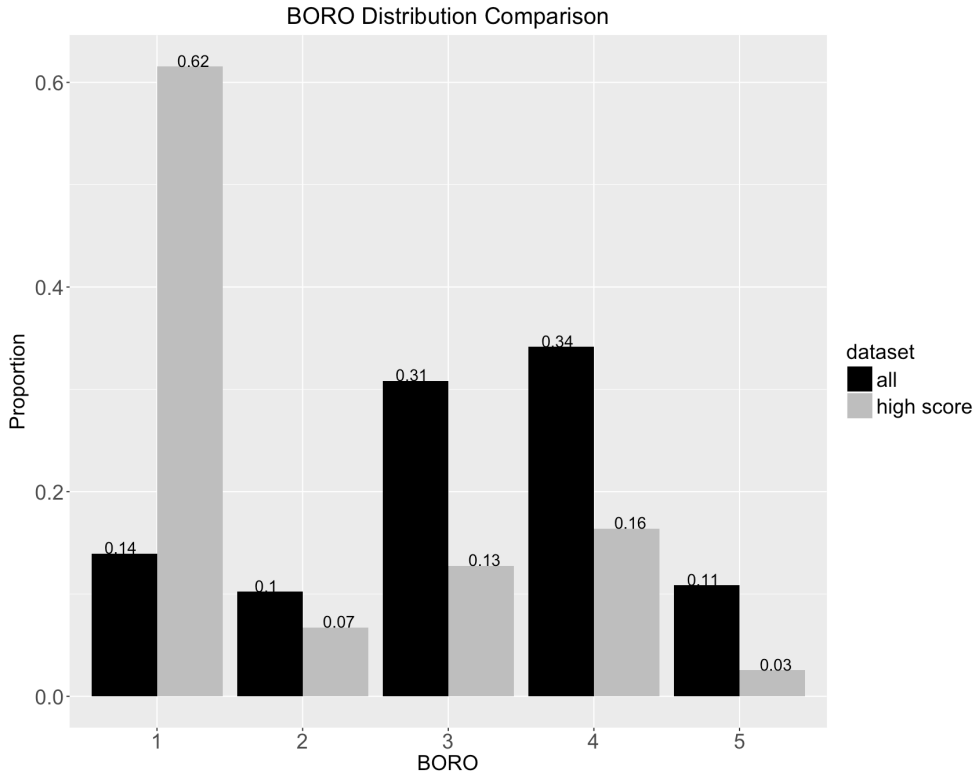
1) We see that the potential fraud properties have significantly higher mean, median and standard deviation values of variables **LTFRONT**, **LTDEPTH**, **STORIES**, **BLDFRONT**, **BLDDEPTH**, **LOT_AREA**, **BLD_VOLUME** (all in green in above table) compared to the complete data. This means these are usually the big buildings of the city.

2) **FULLVAL**, **AVLAND**, **AVTOT**, **EXLAND**, **EXTOT**, **FV_AT**, **AT_ET**, **FV_ET**, **AL_EL** have significantly higher mean, median and standard deviation values of variables in **Top 1%** records when compared to the complete data.

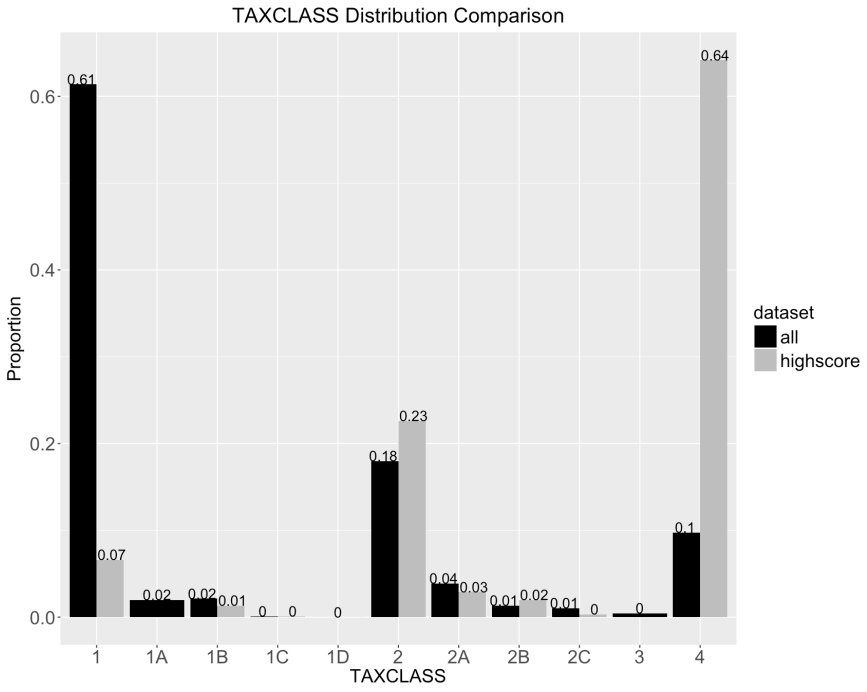
3) The important thing to note is the variable **FV_AT**. The variable gives us the ratio of **FULLVAL/AVTOTAL. FV_AT** whose mean in complete data is 22 but mean in Top 1% records increases to 40. This tells us that the properties in Top 1% records are being **significantly undervalued and hence paying lower taxes** than they should when

compared to the complete data.

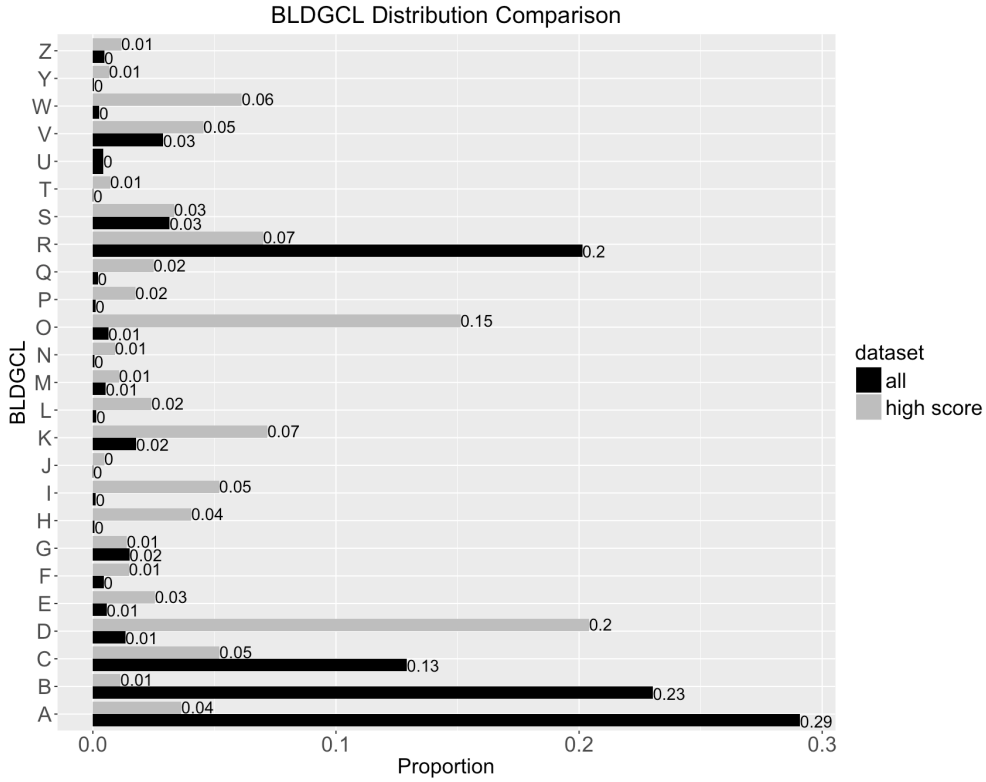
4) The distribution of **BORO** in the top 1% records is very different from that in the whole dataset. Among the top 1% records that got high scores, over 60% of the properties are located in **BORO** 1, which is Manhattan, while in the original dataset, only 14% properties are in that area. This could be caused by the fact that the house price and land price are much higher in Manhattan than in other areas in New York City.



5) Looking at the **TAXCLASS** of the top 1% high score records, we found that **64%** of the properties belong to the **TAXCLASS 4**. But in the whole dataset, there are only **10%** properties in **TAXCLASS 4**. This is reasonable because properties in **TAXCLASS 4** represent “UTILITIES - CEILING RAILROADS” and “ALL OTHERS”, which could have a totally different set of values.



6) The top **1%** properties also have higher proportion of **BLDGCL D** and **O**, comparing to that of the whole dataset. Buildings in **BLDGCL D** are elevator apartments, while those in **BLDGCL O** are office buildings. Both tend to have higher values.



7) OWNER

When we look at the owners of the high score properties, we find that most of the owners are large house agencies or real estate companies. There are also many educational institutions and government entities. Few of these properties belongs to single households.

Top 10 records:

The below tables show the top 10 records.

RECORD	BBLE	BLOCK	LOT	EASEMENT	OWNER	BLDGCL	TAXCLASS	LTFRONT	LTDEPTH	STORIES
53359	1009990019	999	19	NA	DOLP 114 PROPERTIES I	O4	4	125	200	25
55152	4120990001	12099	1	NA	RISINGSAM DITMARS LLC	H9	4	115	366	12
88293	1013081101	1308	1101	NA	BP 399 PARK AVENUE,	R5	4	200	405	42
89293	1012840007	1284	7	NA	KATO KAGAKU CO LTC	O4	4	124	201	45
91536	1013740014	1374	14	NA	CRP/AAC 650 MADISON O	O3	4	200	245	27
94469	1012960046	1296	46	NA	15042 ESTATE BORROWIN	O3	4	420	197	42
101017	1007819002	781	9002	NA	ELI ACQUISITION LLC	O3	4	455	257	31
111320	1013070001	1307	1	NA	375 PARK AVE LP	O4	4	200	302	38
121555	1013100063	1310	63	NA	TOWER 56 REAL ESTATE	O4	4	60	100	33
125615	1012700001	1270	1	NA	SILVER AUTUMN HTL COR	H1	4	100	120	35

RECORD	FULLVAL	AVLAND	AVTOT	ZIP	EXMPTCL	BLDFRONT	BLDDEPTH	FULLVAL_BORO	FULLVAL_EASEMENT	FULLVAL_BLDGCL	FULLVAL_TAXCLASS	FULLVAL_ZIP	FULLVAL_LOT_AREA
53359	180000000	41400000	81000000	10036	NA	125	200	680	403	211	547	703	125
55152	30300000	4590000	13635000	11434	NA	170	100	64	68	5	92	86	2
88293	595000000	49500000	267750000	10022	NA	0	0	2248	1331	4527	1809	2104	82
89293	222000000	19710000	99900000	10017	NA	80	127	839	497	261	675	1021	142
91536	226000000	72000000	101700000	10022	NA	200	245	854	506	265	687	799	82
94469	347000000	50850000	156150000	10017	NA	420	197	1311	776	407	1055	1596	4
101017	310000000	31500000	139500000	10001	NA	354	139	1171	694	364	942	553	2
111320	382000000	42390000	171900000	10022	NA	196	279	1443	855	448	1161	1351	44
121555	91900000	5445000	41355000	10022	NA	60	100	347	206	108	279	325	150
125615	81800000	12150000	36810000	10019	NA	100	120	309	183	13	249	381	91

We examined these records one by one:

1) **RECORD No. 53359** - We can see that it has unusual values of FULLVAL with respect to BORO, BASEMENT, BLDGCL, TAXCLASS, ZIP and LOTAREA. The ratios are higher than 100 and surely indicate that there may be some kind of fraud.

2) **RECORD No. 55152** – Although its FULLVAL with respect to LOTAREA and BLDGCL seems fine, it has unusual values of FULLVAL with respect to BORO, BASEMENT, TAXCLASS, ZIP. The ratios are higher than 50 and surely indicate that there may be some kind of fraud.

3) **RECORD No. 88293** –We can see that it has unusual values of FULLVAL with respect

to BORO, BASEMENT, BLDGCL, TAXCLASS, ZIP and LOTAREA. The ratios are higher than 1000 and is a must pick record for investigation purposes.

4) **RECORD No. 89293** – We can see that it has unusual values of FULLVAL with respect to BORO, BASEMENT, BLDGCL, TAXCLASS, ZIP and LOTAREA. The ratios are higher than 100 and surely indicate that there may be some kind of fraud.

5) **RECORD No. 91536** – We can see that it has unusual values of FULLVAL with respect to BORO, BASEMENT, BLDGCL, TAXCLASS, ZIP and LOTAREA. The ratios are higher than 100 and surely indicate that there may be some kind of fraud.

6) **RECORD No. 94469** – Although its FULLVAL with respect to LOTAREA seems fine. It has unusual values of FULLVAL with respect to BORO, BASEMENT, TAXCLASS, ZIP and BLDGCL. The ratios are higher than 100 and surely indicate that there may be some kind of fraud.

7) **RECORD No. 101017** – Although its FULLVAL with respect to LOTAREA seems fine. It has unusual values of FULLVAL with respect to BORO, BASEMENT, TAXCLASS, ZIP and BLDGCL. The ratios are higher than 100 and surely indicate that there may be some kind of fraud.

8) **RECORD No. 111320** – We can see that it has unusual values of FULLVAL with respect to BORO, BASEMENT, BLDGCL, TAXCLASS, ZIP and LOTAREA. Most ratios are higher than 100 and surely indicate that there may be some kind of fraud.

9) **RECORD No. 121555** – We can see that it has unusual values of FULLVAL with respect to BORO, BASEMENT, BLDGCL, TAXCLASS, ZIP and LOTAREA. Most ratios are higher than 100 and surely indicate that there may be some kind of fraud.

10) **RECORD No. 125615** – Although its FULLVAL with respect to BLDGCL seems fine. It has unusual values of FULLVAL with respect to BORO, BASEMENT, TAXCLASS, ZIP and LOTAREA. Most ratios are higher than 100 and surely indicate that there may be some kind of fraud.

NOTE: The top 10 records that were captured by using the fraud score algorithms had a record which belongs to an exemption category and is owned by US Government so we have removed it from the list of potential frauds.

RECORD	BBLE	BLOCK	LOT	EASEMENT	OWNER	BLDGCL	TAXCLASS	LTFRONT	LTDEPTH	STORIES	FULLVAL	AVLAND
78804	3085900700	8590	700	NA	U S GOVERNMENT OWNRD	V9	4	117	108	NA	4326303700	1946836665

FULLVAL	AVLAND	AVTOT	EXLAND	EXTOT	EXCD1	ZIP	EXMPTCL	BLDFRONT	BLDDEPTH	EXCD2
4326303700	1946836665	1946836665	1946836665	1946836665	2231	NA	X1	0	0	NA

APPENDIX

City of New York Property Valuation and Assessment Data

Data Quality Report

Summary

File description:

The City of New York Property Valuation and Assessment Data file is a public available dataset posted by the Department of Finance on the City of New York Open Data website. The dataset contains the records of more than 1 million properties across the city of New York and information on their sizes, values, owners, building classes, tax classes, etc.

File Name:

City of New York Property Valuation and Assessment Data

Data Source:

City of New York Open Data Website (https://data.cityofnewyork.us/Housing-Development/Property-Valuation-and-Assessment-Data/rgy2-tti8)

Number of Records:

1,048,575 records

Number of Fields:

30 variables in total – 13 categorical variables, 14 numeric variables, 2 text variables, 1 date variables

Time of Records:

November 2011

Fields Explanation

Field 1

Field Name: RECORD

Description:
RECORD is a categorical variable. It works as the ordinal reference number for each property record.

Unique Values:
1,048,575 unique values, ranging from 1 to 1,048,575. No repeated values or missing values exist.

Field 2

Field Name: BBLE

Description:
BBLE is a nominal categorical variable with 10 or 11 digits. It is the concatenation of BORO code (1 digit), BLOCK code (5 digit), LOT code (4 digit) and EASEMENT code (1 digit if exists).

Unique Values:
1,048,575 unique values. No repeated values or missing values exist.

Field 3

Field Name: BLOCK

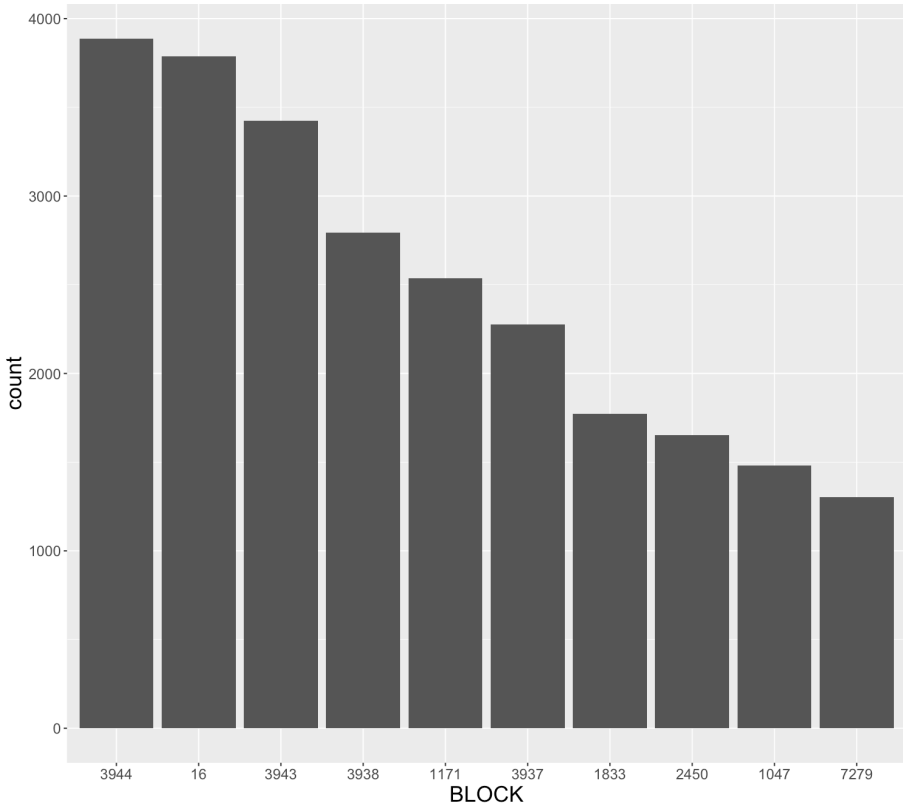
Description:

BLOCK is a categorical variable with 1 to 5 digits. It represents the property's corresponding block code in a certain borough. For each borough, there is a valid block code range:

MANHATTAN	1 TO 2,255
BRONX	2,260 TO 5,958
BROOKLYN	1 TO 8,955
QUEENS	1 TO 16,350
STATEN ISLAND	1 TO 8,050

Unique Values:

BLOCK has 13949 unique values, ranging from 1 to 16350. No missing values. The top 10 most frequently appeared BLOCK code is shown below.



BLOCK	Percentage(%)
3944	0.37
16	0.36
3943	0.32
3938	0.27
1171	0.24
3937	0.21
1833	0.17
2450	0.16
1047	0.14
7279	0.12

Field 4

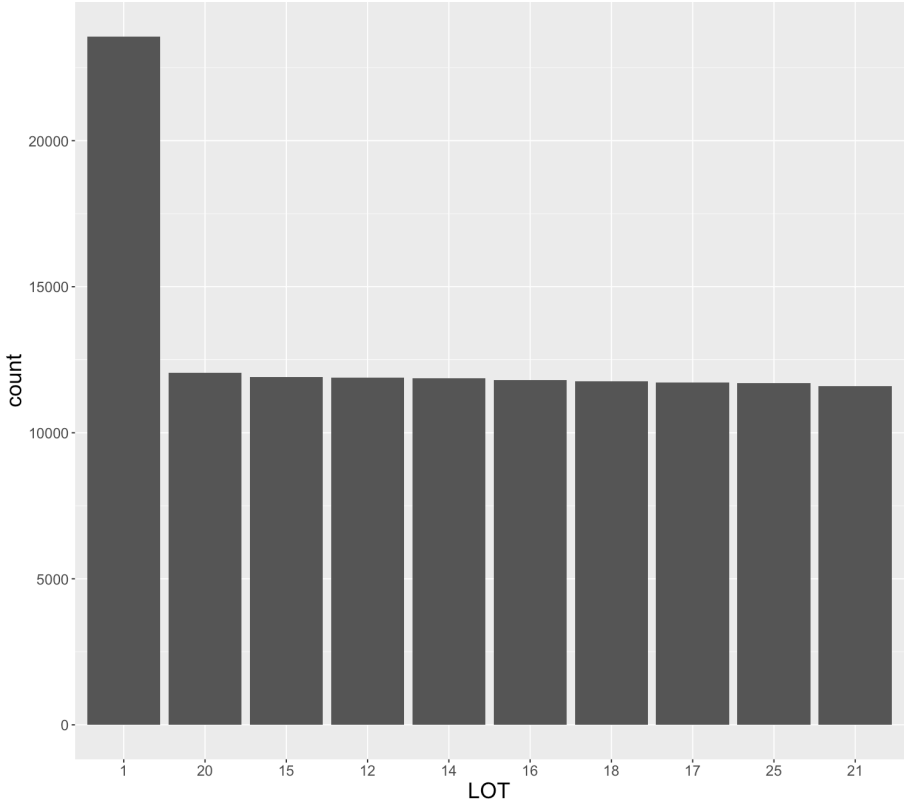
Field Name: LOT

Description:

LOT is a categorical variable with 1 to 4 digits. It represents the property's lot code within its borough and block.

Unique Values:

LOT has 6366 unique values, ranging from 1 to 9978. No missing values. The top 10 most frequently appeared LOT code is shown below.



LOT	Percentage(%)
1	2.25
20	1.15
15	1.14
12	1.13
14	1.13
16	1.13
18	1.12
17	0.12
25	1.12
21	1.11

Field 5

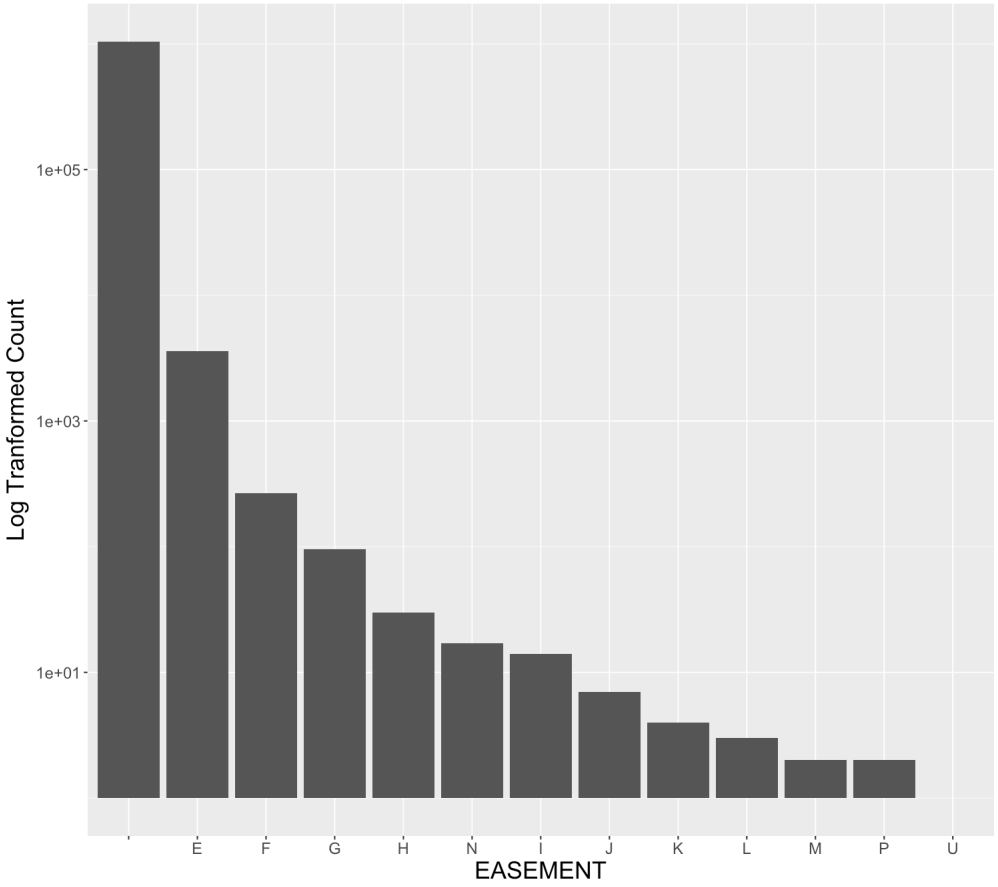
Field Name: EASEMENT

Description:

EASEMENT is a nominal categorical variable representing the property's easement type.

Unique values:

EASEMENT has 13 levels – "", "E", "F", "G", "H", "I", "J", "K", "L", "M", "N", "P", "U". The null value indicates the property does not have any special easement. No missing values exist. The sorted bar chart with log transformed y axis is shown below.



Level	Counts
	1044532 (99.6%)
E	3603
F	265
G	95
H	30
I	14
J	7
K	4
L	3
M	2
N	17
P	2
U	1

Field 6

Field Name: OWNER

Description:

OWNER is a text variable indicating the owner of the property.

Unique Values:

OWNER has 847055 unique values. In the OWNER field, 31081 properties have the value “”, indicating possible missing values. No missing values exist. The top 10 most frequently occurred OWNER names are:

Owner	Count	Percentage(%)
	31081	2.96
PARKCHESTER PRESERVAT	6021	0.57
PARKS AND RECREATION	3358	0.32
DCAS	2053	0.20
HOUSING PRESERVATION	1900	0.18
CITY OF NEW YORK	1189	0.11
NEW YORK CITY HOUSING	1014	0.10
BOARD OF EDUCATION	1003	0.10
CNY/NYCTA	975	0.09
NYC HOUSING PARTNERSH	747	0.07

Field 7

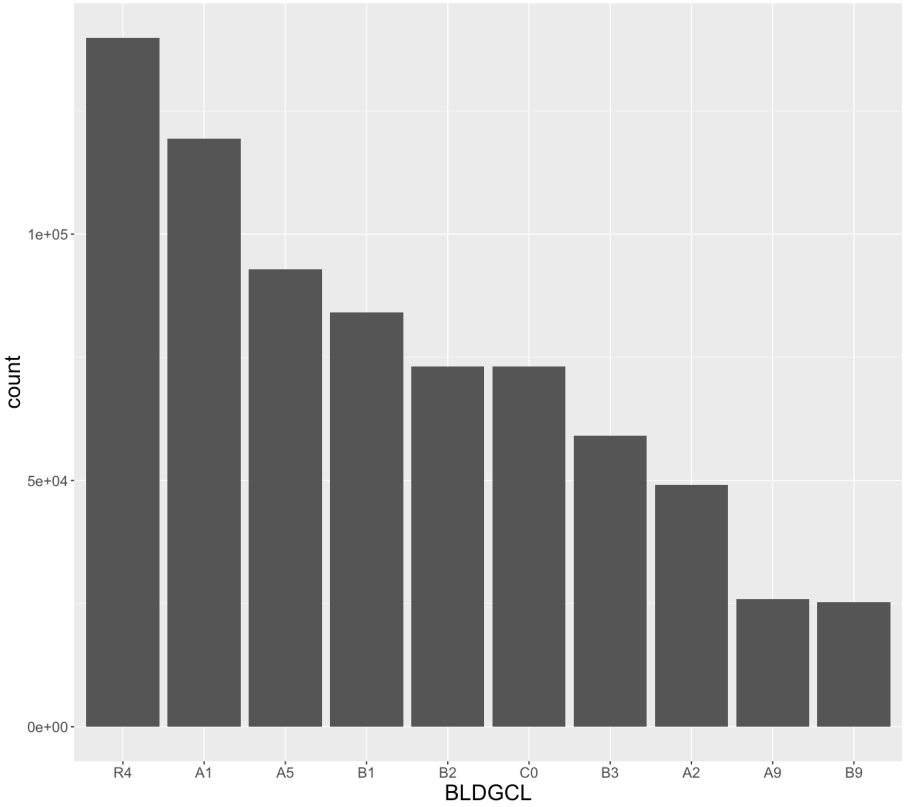
Field Name: BLDGCL

Description:

BLDGCL is a nominal categorical variable indicating the building class.

Unique Values:

BLDGCL has 200 unique levels. Each level has 2 digits – the first digit is a character from A to Z, the second digit is a number from 0 to 9. No missing values exist. The top 10 most frequently occurred BLDGCL is shown in below:



BLDGCL	Percentage(%)
R4	13.3
A1	11.4
A5	8.9
B1	8
B2	7
C0	8
B3	5.6
A2	4.7
A9	2.5
B9	2.4

Field 8

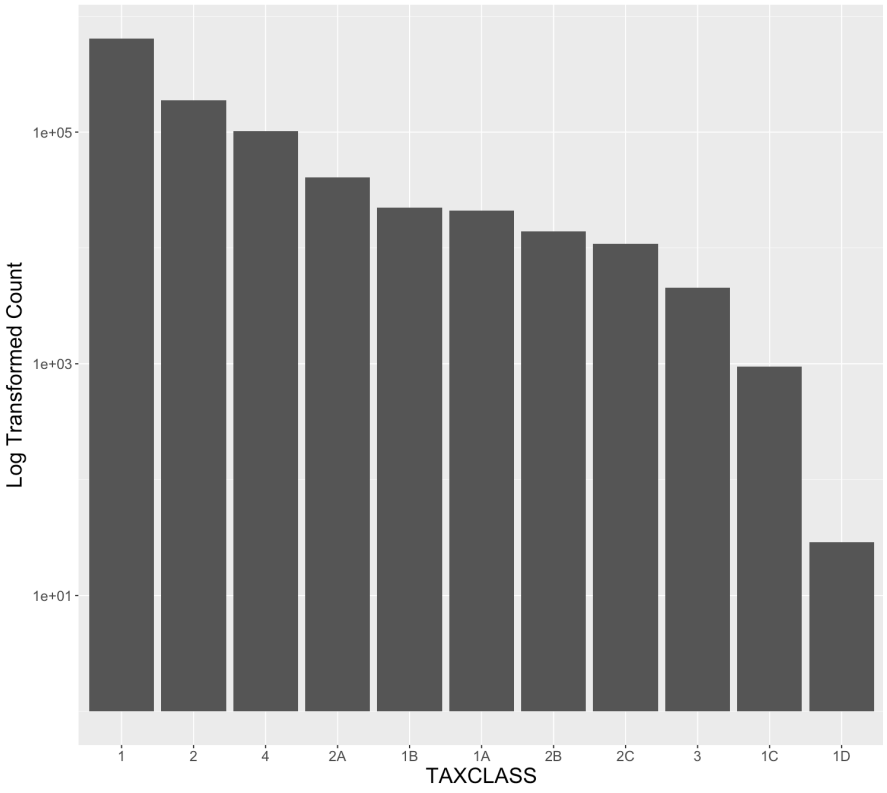
Field Name: TAXCLASS

Description:

TAXCLASS is a categorical variable indicating the tax class of the property.

Unique Values:

TAXCLASS has 11 unique levels – “1”, “1A”, “1B”, “1C”, “1D”, “2”, “2A”, “2B”, “2C”, “3”, and “4”. No missing values exist. Sorted TAXCLASS levels are shown below:



Level	Percentage(%)
1	61.4
2	18.0
4	9.8
2A	3.9
1B	2.1
1A	2.0
2B	1.3
2C	1.0
3	0.4
1C	0.1
1D	0.0

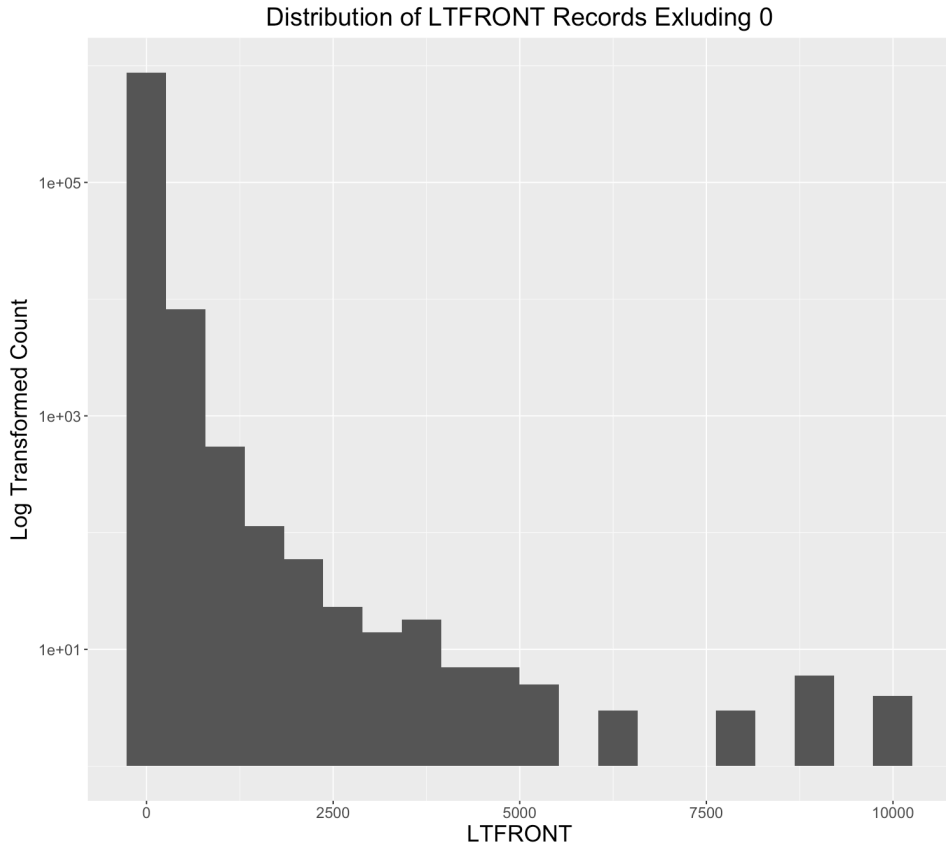
Field 9

Field Name: LTFRONT

Description:
LTFRONT is a numeric variable representing the length of lot frontage in feet.

Unique Values:
LTFRONT has 1277 unique values ranging from 0 to 9999. No missing values exist. There are 168,867 records of 0 LTFRONT, and a LTFRONT of 0 may indicate missing value. The statistics and distribution excluding 0 records are shown as below.

Minimum	1
Maximum	9999
Median	25
Mean	43.12
Mode	20
SD	78.62



Field 10

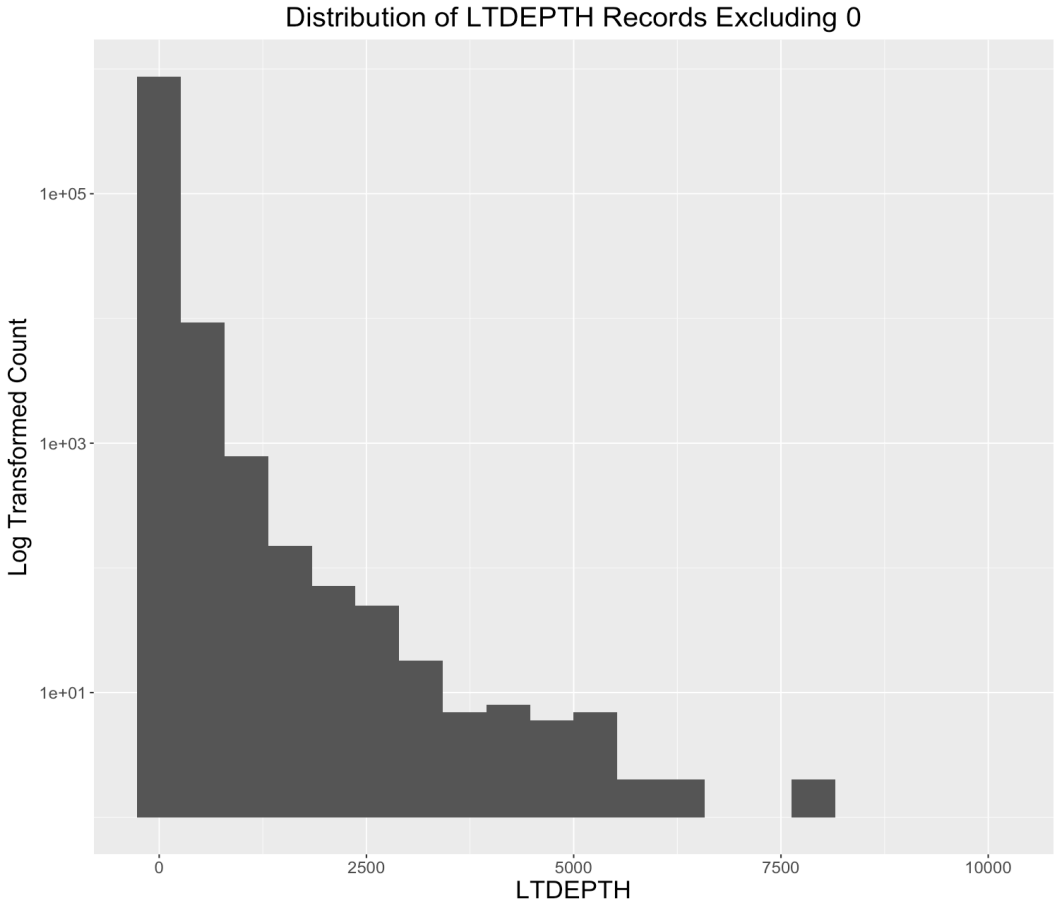
Field Name: LTDEPTH

Description:

LTDEPTH is a numeric variable representing the length of lot depth in feet.

Unique Values:
LTDEPTH has 1336 unique values ranging from 0 to 9999. No missing values exist. There are 169,888 records of 0 LTDEPTH, and a LTDEPTH of 0 may indicate missing value. The statistics and distribution excluding 0 records are shown as below.

Minimum	1
Maximum	9999
Median	100
Mean	105.34
Mode	100
SD	70.71



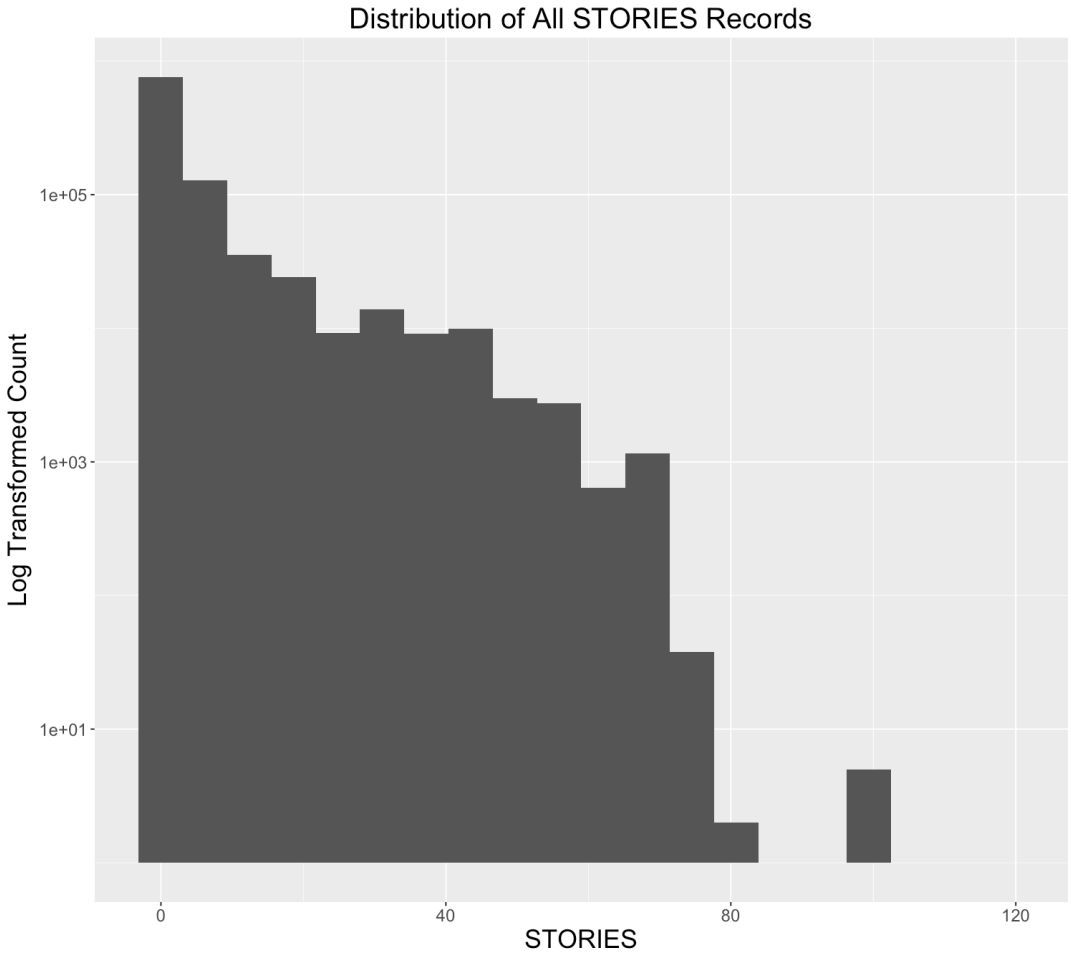
Field 11

Field Name: STORIES

Description:
STORIES is a numeric variable representing the number of stories of the property.

Unique Values:
STORIES has 112 unique values ranging from 1 to 119. There are 52,142 missing values in the STORIES field. The statistics and distribution are shown as below.

Minimum	1
Maximum	119
Median	2
Mean	5.06
Mode	2
SD	8.43



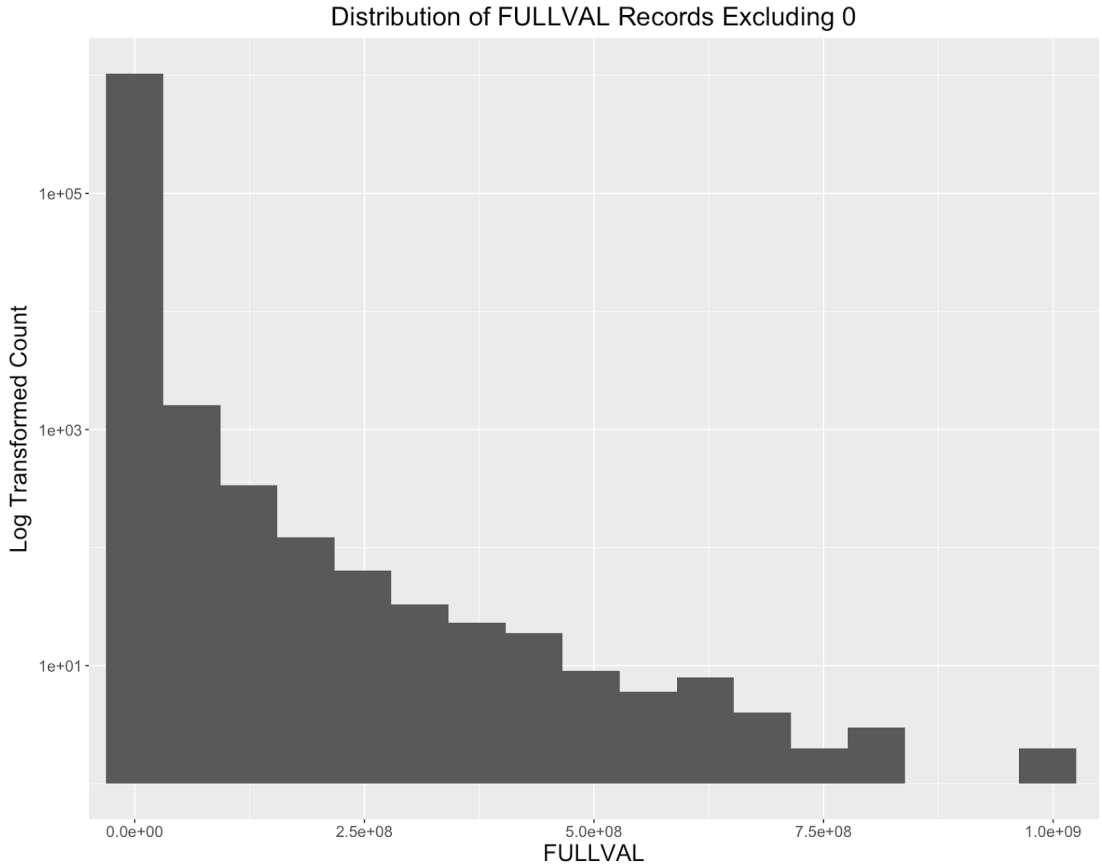
Field 12

Field Name: FULLVAL

Description:
FULLVAL is a numeric variable representing the full value of the property.

Unique Values:
FULLVAL has 108277 unique values ranging from 0 to about 6,000,000,000. There are 12,762 properties with the FULLVAL of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown as below.

Minimum	4
Maximum	6.15E+09
Median	45000
Mean	8.91E+05
Mode	502000
SD	1.17E+07

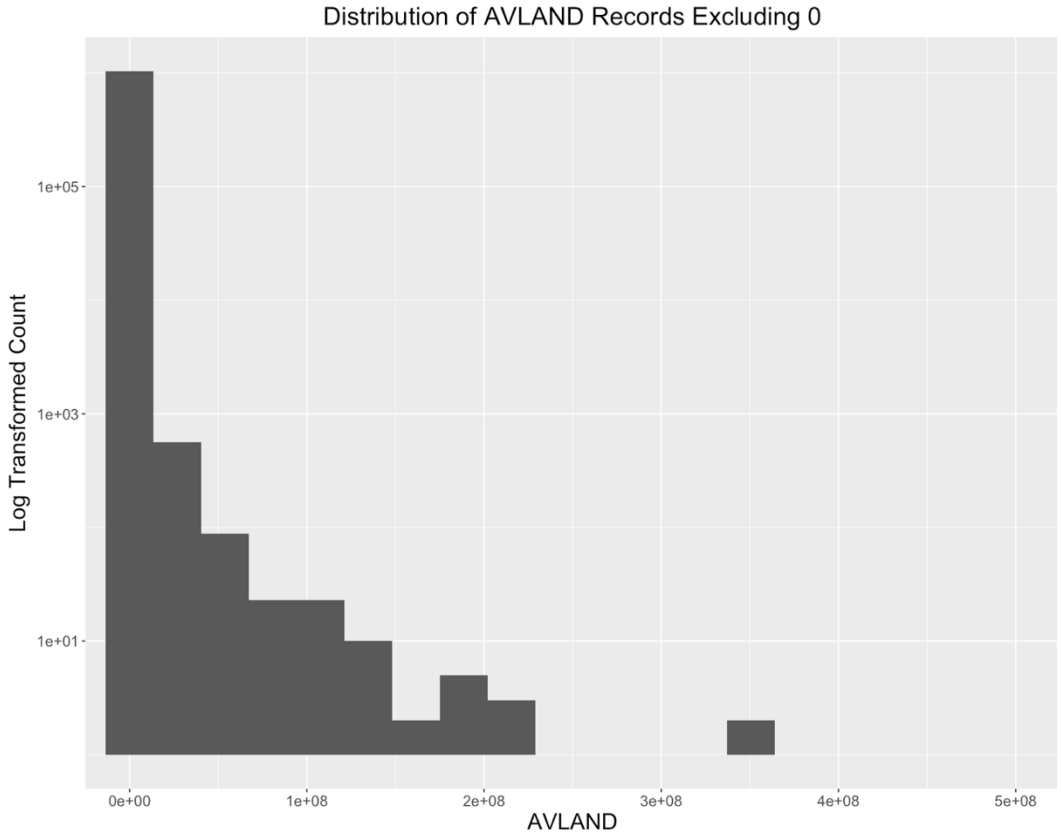


Field 13
Field Name: AVLAND

Description:
AVLAND is a numeric variable representing the assessed value of the land.

Unique Values:
AVLAND has 70,529 unique values ranging from 0 to about 2,700,000,000. There are 12,764 properties with the AVLAND of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown as below.

Minimum	1
Maximum	2.67E+09
Median	13751
Mean	86054.72
Mode	45000
SD	4.10E+06



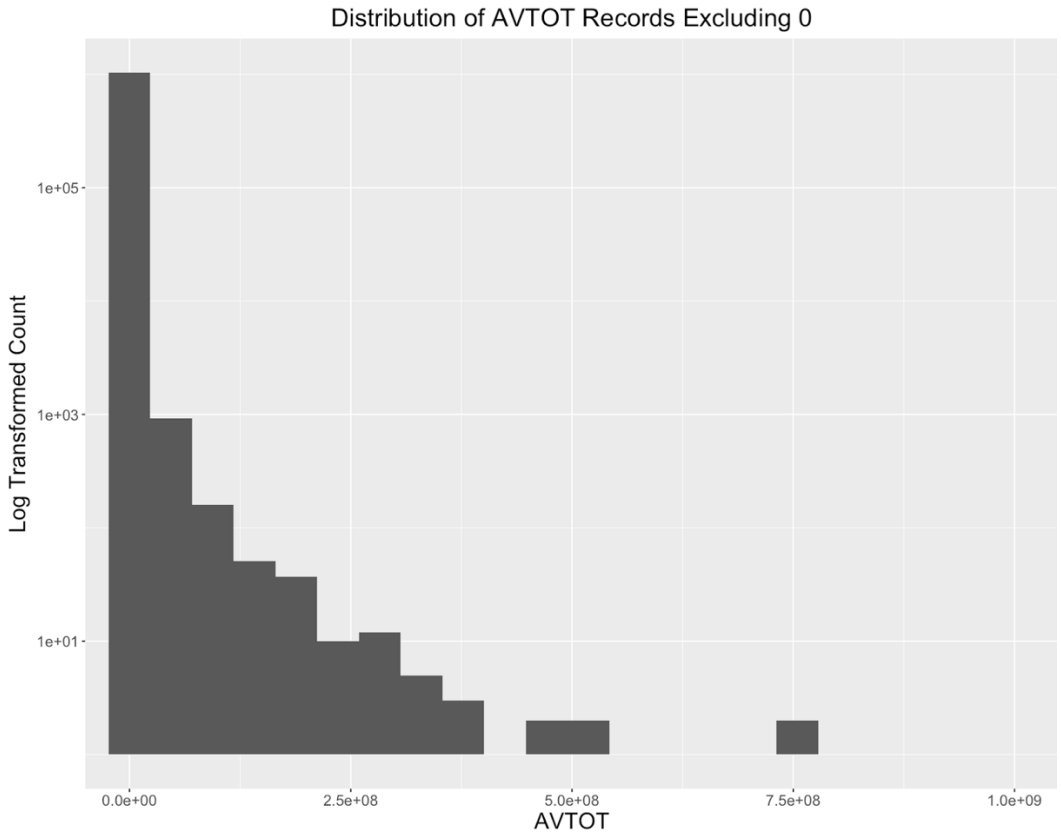
Field 14

Field Name: AVTOT

Description:
AVTOT is a numeric variable representing the assessed total value of the property.

Unique Values:
AVTOT has 112294 unique values ranging from 0 to about 4,700,000,000. There are 12,762 properties with the AVTOT of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown as below.

Minimum	1
Maximum	4.67E+09
Median	25560
Mean	233601.3
Mode	16588
SD	6.99E+06



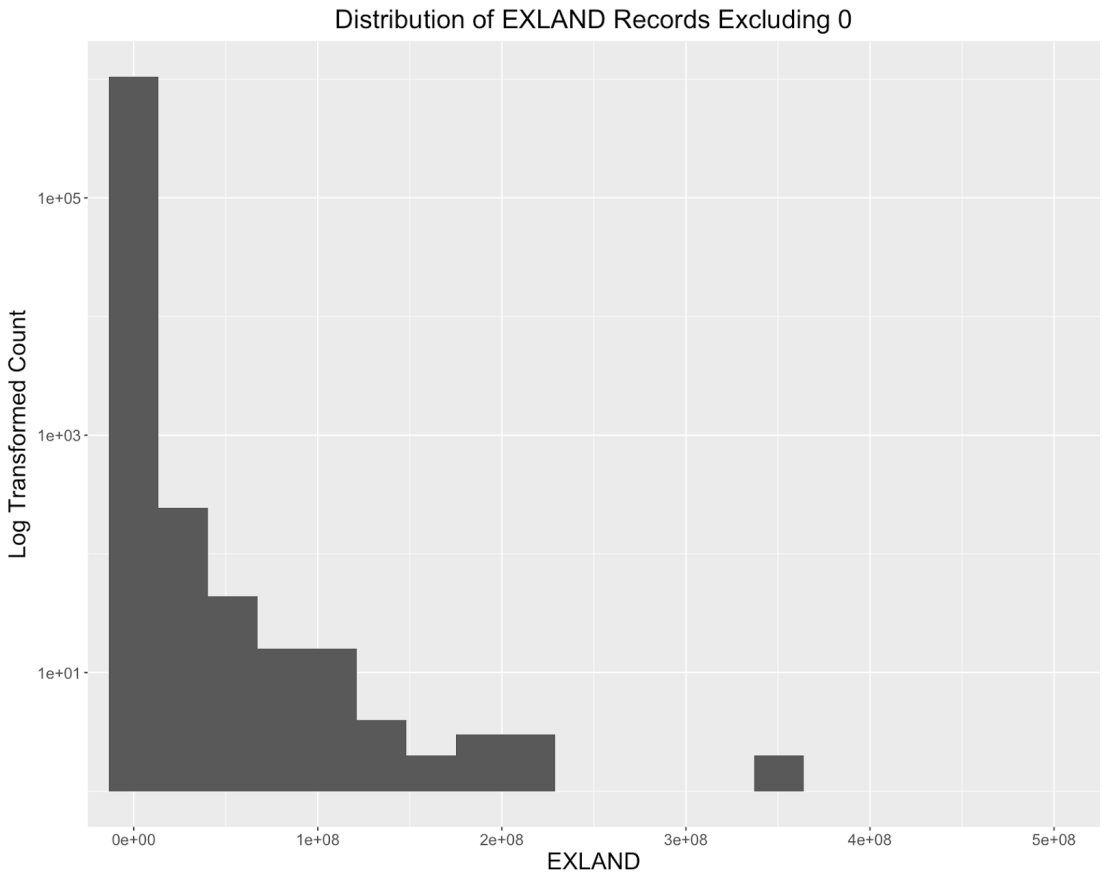
Field 15

Field Name: EXLAND

Description:
EXLAND is a numeric variable representing the value of the exempt land. The value of EXLAND is always smaller or equal to AVLAND.

Unique Values:
EXLAND has 33186 unique values ranging from 0 to about 2,700,000,000. There are 484,224 properties with the EXLAND of 0 in the dataset. No missing values exist. The statistics and distribution excluding 0 records are shown as below.

Minimum	1
Maximum	2.67E+09
Median	1620
Mean	68397.01
Mode	1620
SD	5485336



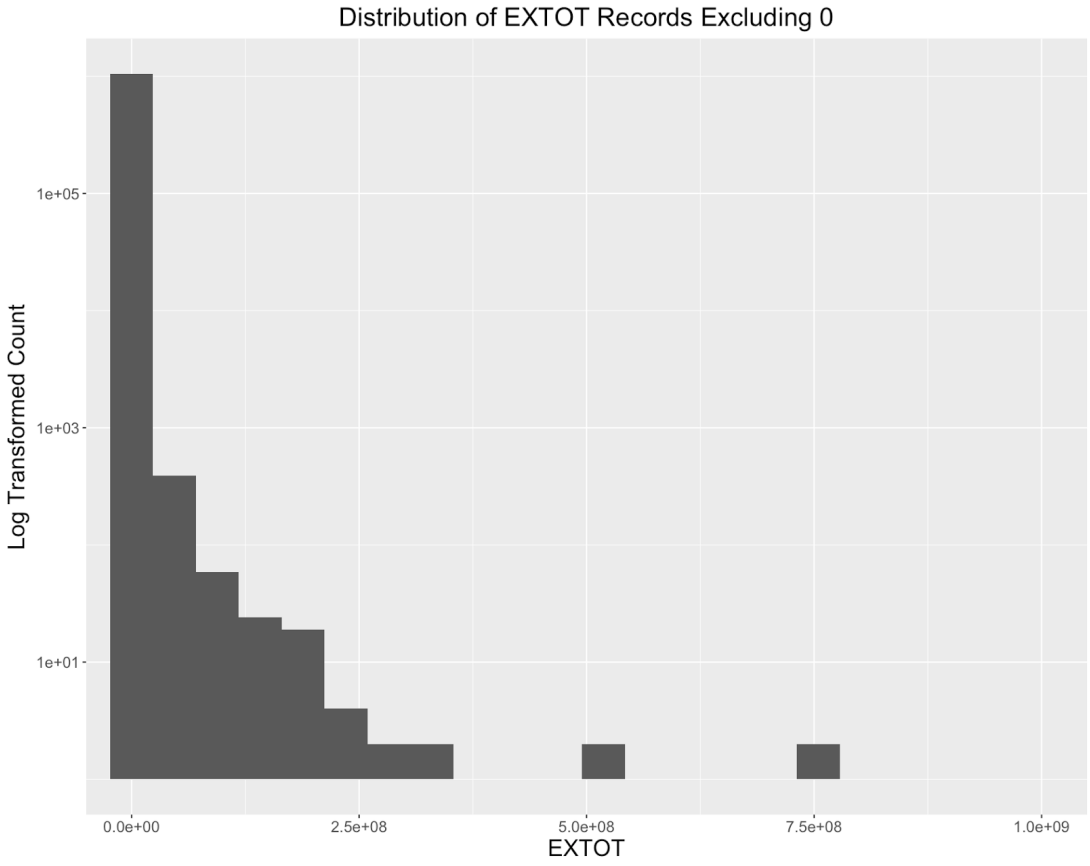
Field 16

Field Name: EXTOT

Description:
EXTOT is a numeric variable representing the total value of the exempt property. The value of EXTOT is always smaller or equal to AVTOT.

Unique Values:
EXTOT has 63805 unique values ranging from 0 to about 4,700,000,000. There are 425,999 properties with the EXTOT of 0 in the dataset. No missing values exist. . The statistics and distribution excluding 0 records are shown as below.

Minimum	1
Maximum	4.67E+09
Median	1620
Mean	155867.1
Mode	1620
SD	8536636

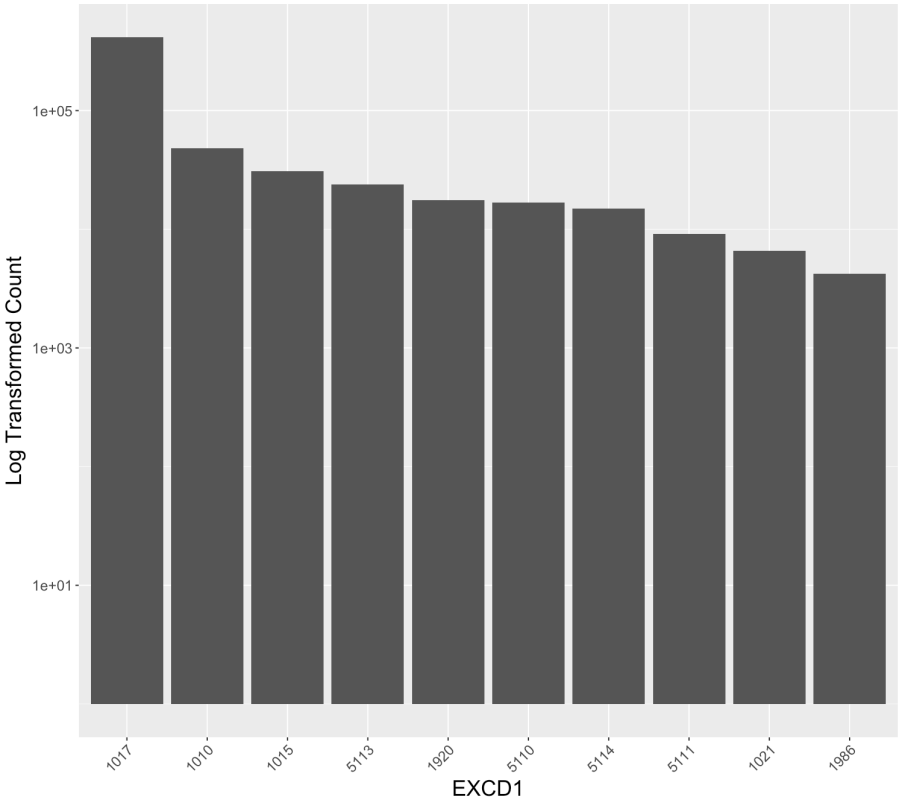


Field 17

Field Name: EXCD1

Description:
EXCD1 is a categorical variable, possibly representing the code for the exempt reasons.

Unique Values:
EXTOT has 130 levels, taking 4-digit numbers from 1010 to 7170. There are 425,933 missing values exist. For all properties that hold missing value in EXCD1, their values in both EXLAND and EXTOT fields are 0. The top 20 most frequently occurred EXCD1 values are shown below.



EXCD1	Percentage(%)
1017	39.5
1010	4.6
1015	2.9
5113	2.3
1920	1.7
5110	1.6
5114	1.4
5111	8.7
1021	6.3
1986	4.0

Field 18

Field Name: STADDR

Description:

STADDR is a text variable, representing the street address of the property.

Unique values:

STADDR has 820,638 unique values. No missing values exist in this field. However, there are 641 records with the value of “” (null) in the STADDR field, indicating missing values.
The top 10 most frequently occurred STADDR values are:

Address	Counts
501 SURF AVENUE	902
330 EAST 38 STREET	817
322 WEST 57 STREET	720
155 WEST 68 STREET	671
20 WEST 64 STREET	657
1 IRVING PLACE	650
	641
220 RIVERSIDE BOULEVARD	628
360 FURMAN STREET	599
200 EAST 66 STREET	585

Field 19

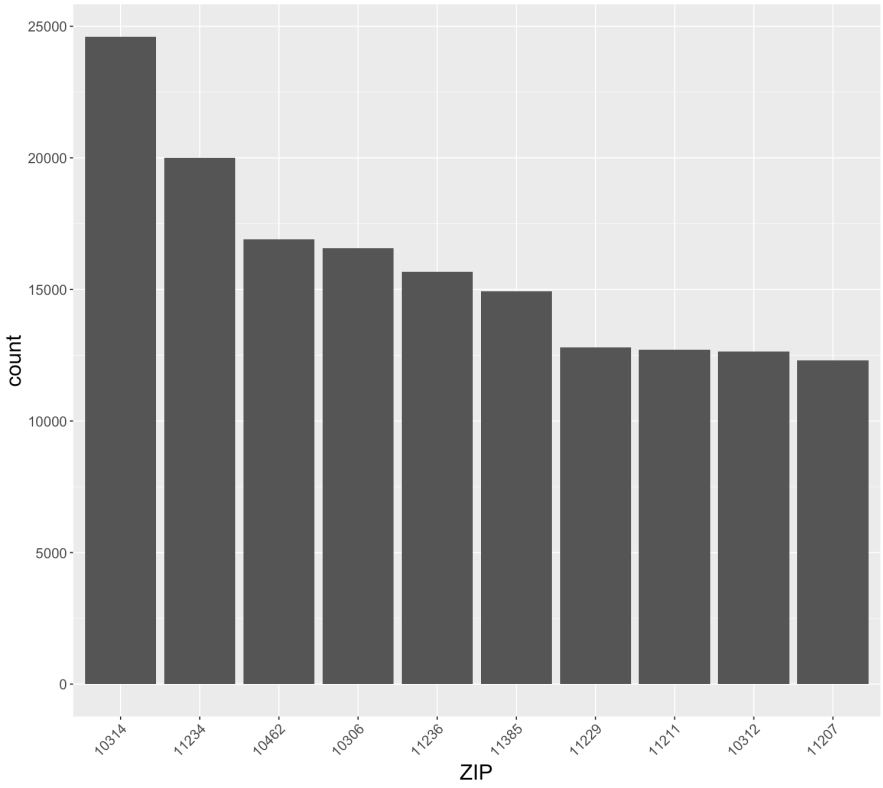
Field Name: ZIP

Description:

ZIP is a categorical variable, recording the zipcode of the property.

Unique Values:

ZIP has 197 unique values and 26,356 missing values. There are three obvious anomaly records with ZIP of 33803, which should be in Florida. The top 20 most frequently occurred ZIP values are:



ZIP	Percentage(%)
10314	2.3
11234	1.9
10462	1.6
10306	1.6
11236	1.5
11385	1.4
11229	1.2
11211	1.2
10312	1.2
11207	1.2

Field 20

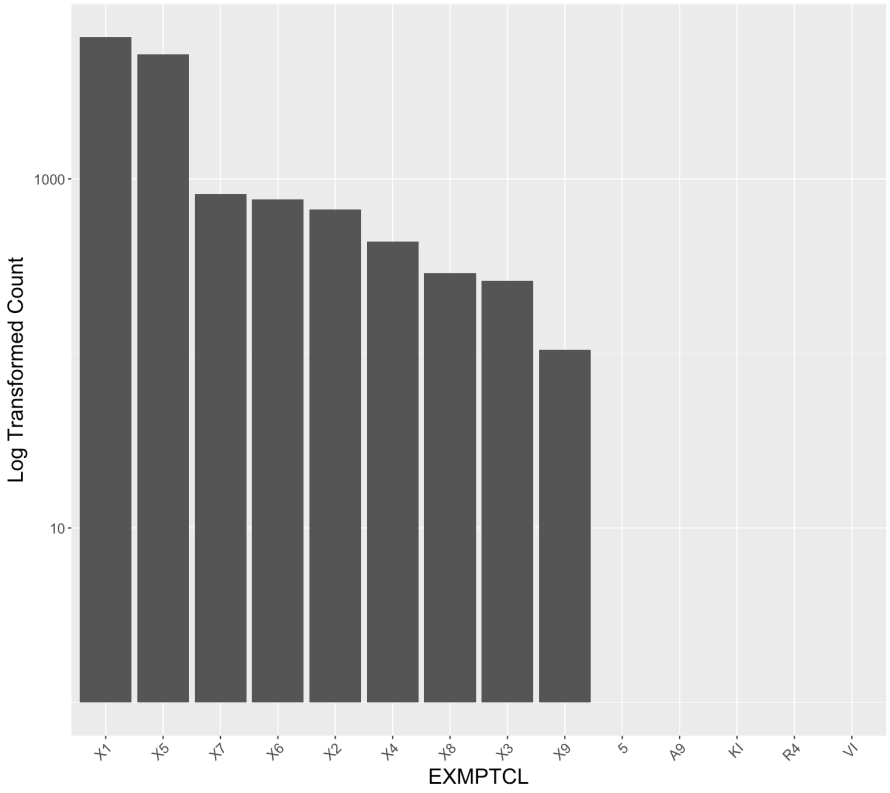
Field Name: EXMPTCL

Description:

EXMPTCL is a nominal categorical variable, representing the exempt class, which is used for exempt properties only.

Unique Values:

EXMPTCL has 15 levels- “”, “5”, “A9”, “KI”, “R4”, “VI”, “X1”, “X2”, “X3”, “X4”, “X5”, “X6”, “X7”, “X8”, and “X9”. 1,033,583 properties take “” value in EXMPTCL. No missing values exist. The sorted bar chart is shown below.



EXMPTCL	Percentage(%)
X1	43.41
X5	34.41
X7	5.46
X6	5.07
X2	4.44
X5	2.92
X8	1.93
X3	1.73
X9	0.70
5	0.01
A9	0.01
KI	0.01
R4	0.01
VI	0.01

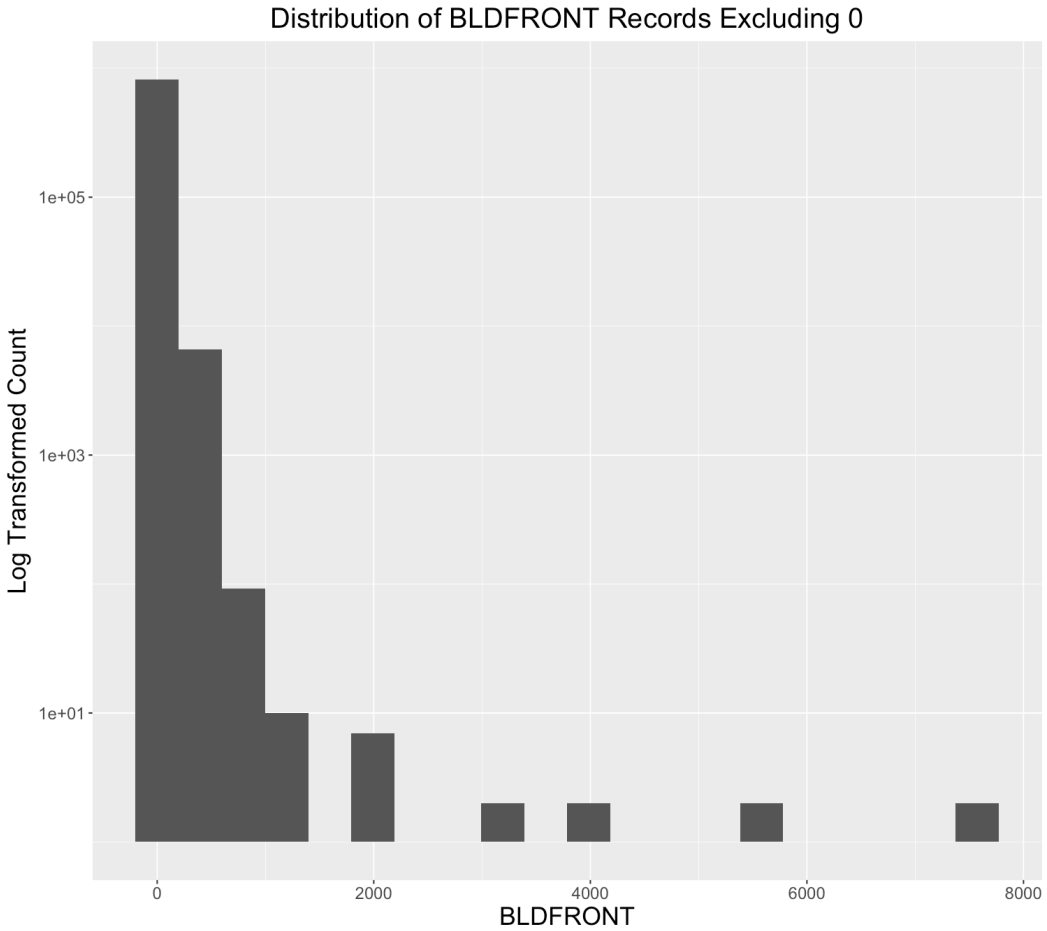
Field 21

Field Name: BLDFRONT

Description:
BLDFRONT is a numeric variable representing the length of building frontage in feet.

Unique Values:
BLDFRONT has 610 unique values ranging from 0 to 7575. No missing values exist. However, there are 224,661 records with value 0, which could be in fact missing values. The statistics and distribution excluding all records with 0 BLDFRONT are shown as below.

Minimum	1
Maximum	7575
Median	20
Mean	29.29
Mode	20
SD	38.03



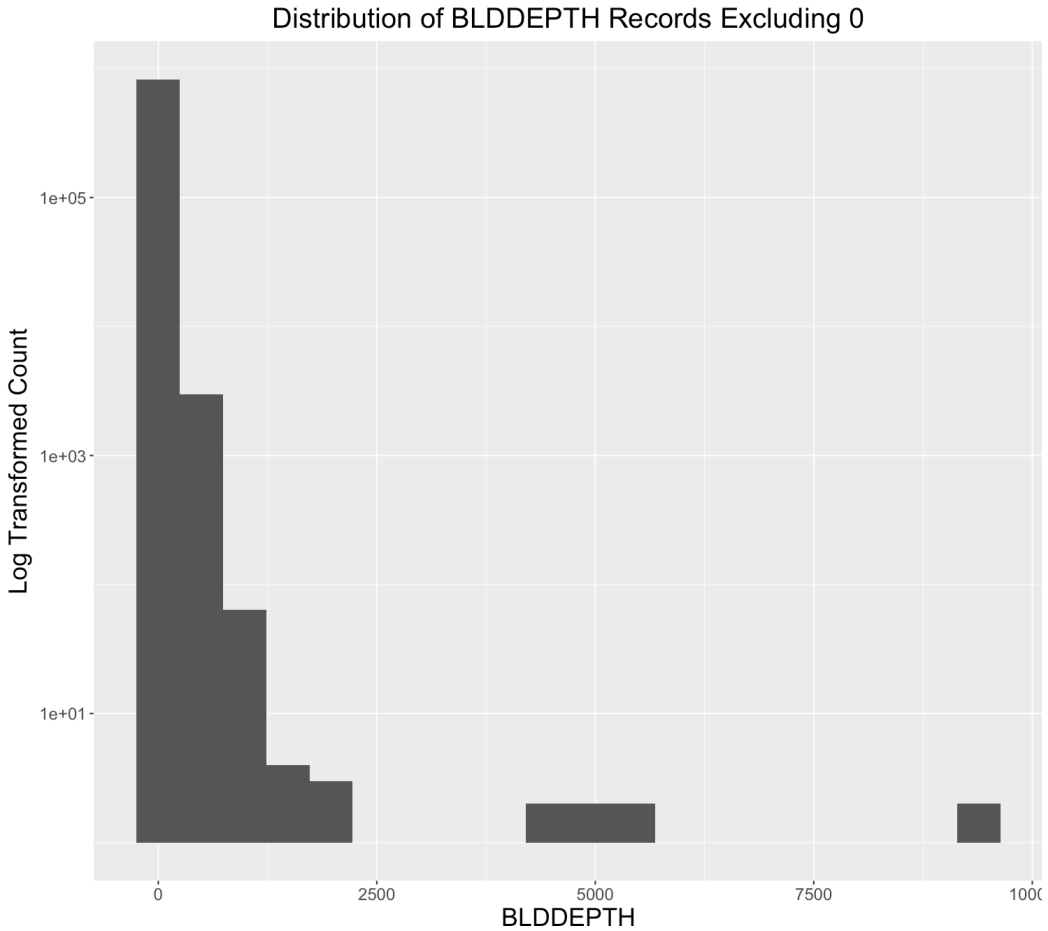
Field 22

Field Name: BLDDEPTH

Description:
BLDDEPTH is a numeric variable representing the length of building depth in feet.

Unique Values:
BLDDEPTH has 620 unique values ranging from 0 to 9393. No missing values exist. However, there are 224,699 records with value 0, which could be in fact missing values. The statistics and distribution excluding all records with 0 BLDFRONT are shown as below.

Minimum	1
Maximum	9393
Median	44
Mean	51.00
Mode	40
SD	42.42



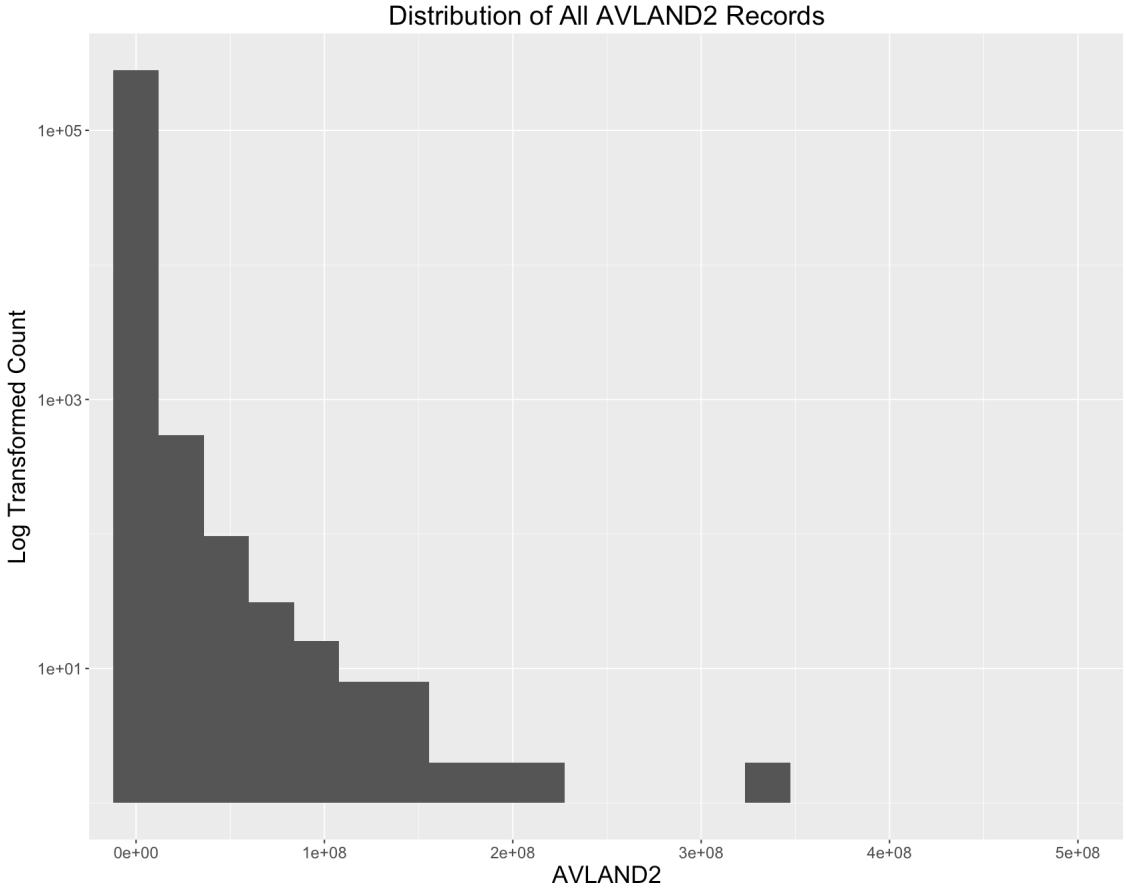
Field 23

Field Name: AVLAND2

Description:
AVLAND2 is a numeric variable representing the assessed value of the land. It could be the updated assessed value compared to AVLAND. Most values of AVLAND2 are lower than their corresponding values of AVLAND.

Unique Values:
AVLAND has 58,170 unique values ranging from 3 to about 2,300,000,000. There are 767,609 records of missing values in the AVLAND2 field. The statistics is shown as below.

Minimum	3
Maximum	2.37E+09
Median	20059
Mean	2.46E+05
Mode	2408
SD	6.20E+06



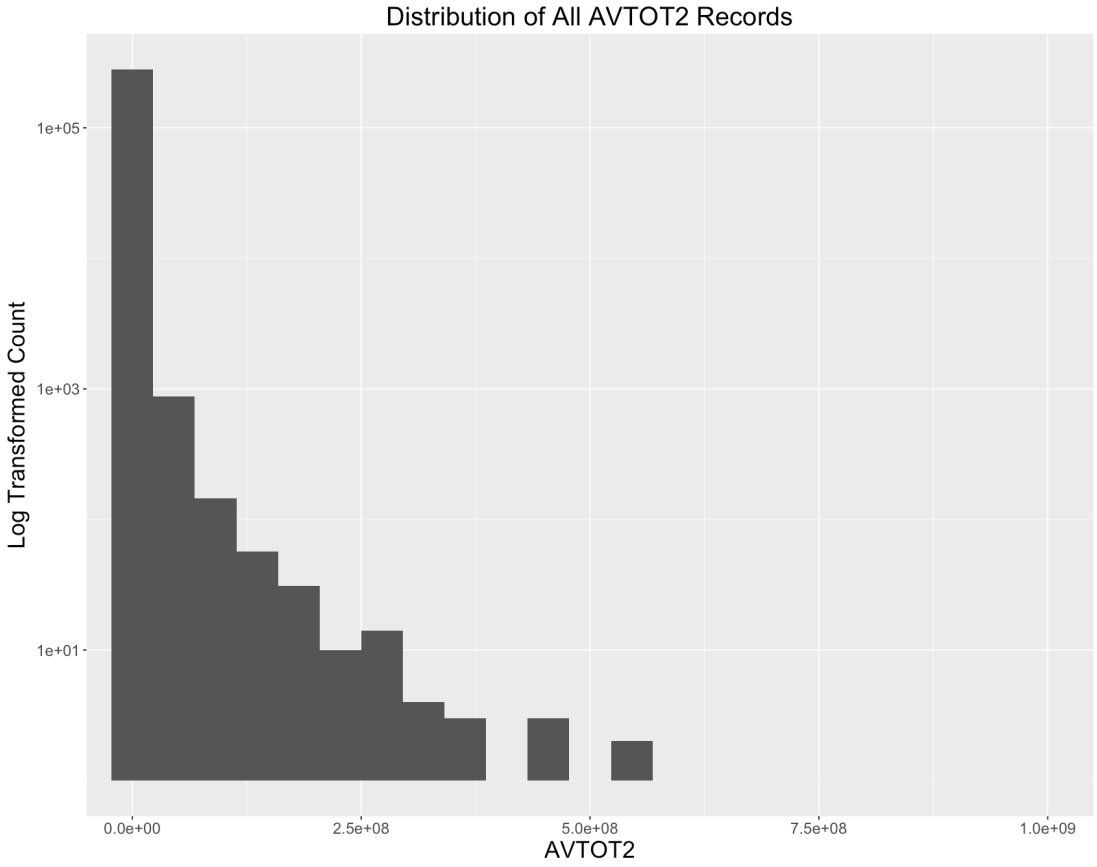
Field 24

Field Name: AVTOT2

Description:
AVTOT2 is a numeric variable representing the assessed total value of the property. It could be the updated assessed value compared to AVTOT. Most AVTOT2 values are smaller than or equal to their corresponding AVTOT value.

Unique Values:
AVTOT2 has 110,891 unique values ranging from 3 to about 4,500,000,000. There are 767,603 missing values in the AVTOT2 field. The statistics is shown as below.

Minimum	3
Maximum	4.50E+09
Median	80010
Mean	7.16E+05
Mode	750
SD	1.17E+07



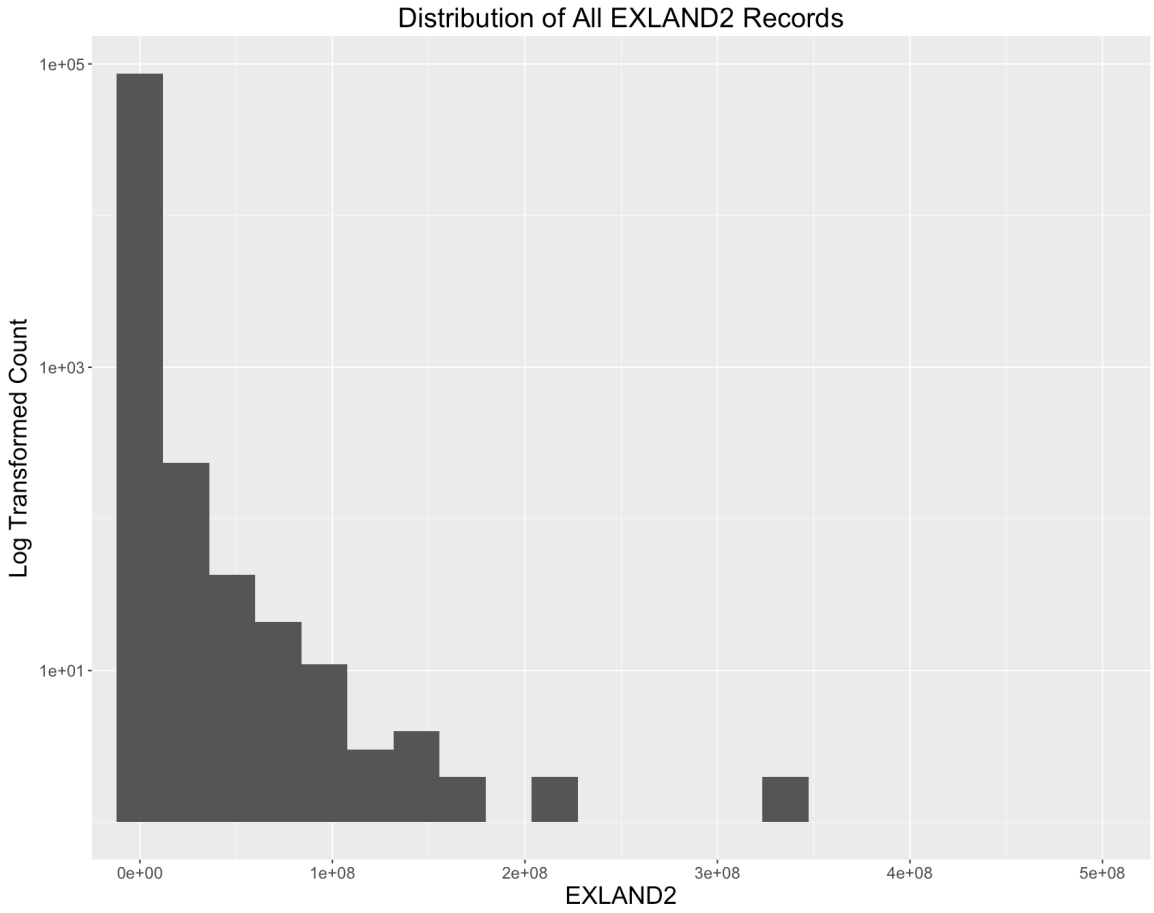
Field 25

Field Name: EXLAND2

Description:
EXLAND2 is a numeric variable representing the value of the exempt land. It could be the updated assessed value compared to EXLAND. Most EXLAND2 values are lower than their corresponding EXLAND values.

Unique Values:
EXLAND2 has 21,997 unique values ranging from 7 to about 2,400,000,000. There are 961,900 missing values in the EXLAND2 field. The statistics is shown as below.

Minimum	7
Maximum	4.50E+09
Median	37116
Mean	6.58E+05
Mode	2090
SD	1.61E+07



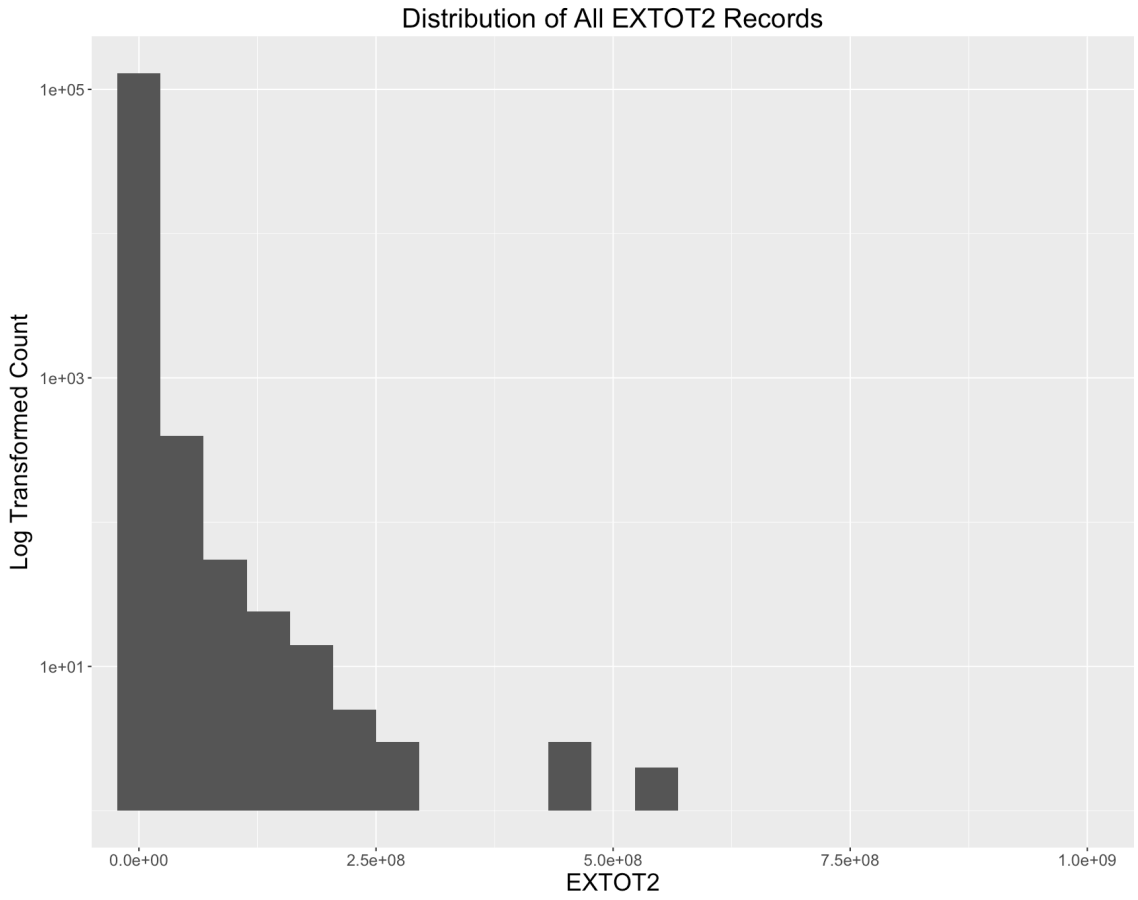
Field 26

Field Name: EXTOT2

Description:
EXTOT2 is a numeric variable representing the total value of the exempt property. It could be the updated assessed value compared to EXTOT. Most EXTOT2 values are lower than their corresponding EXTOT values.

Unique values:
EXTOT2 has 48107 unique values ranging from 7 to about 4,500,000,000. There are 918,642 missing values in the EXTOT2 field. The statistics is shown as below.

Minimum	7
Maximum	4.50E+09
Median	37116
Mean	6.58E+05
Mode	2090
SD	1.61E+07



Field 27

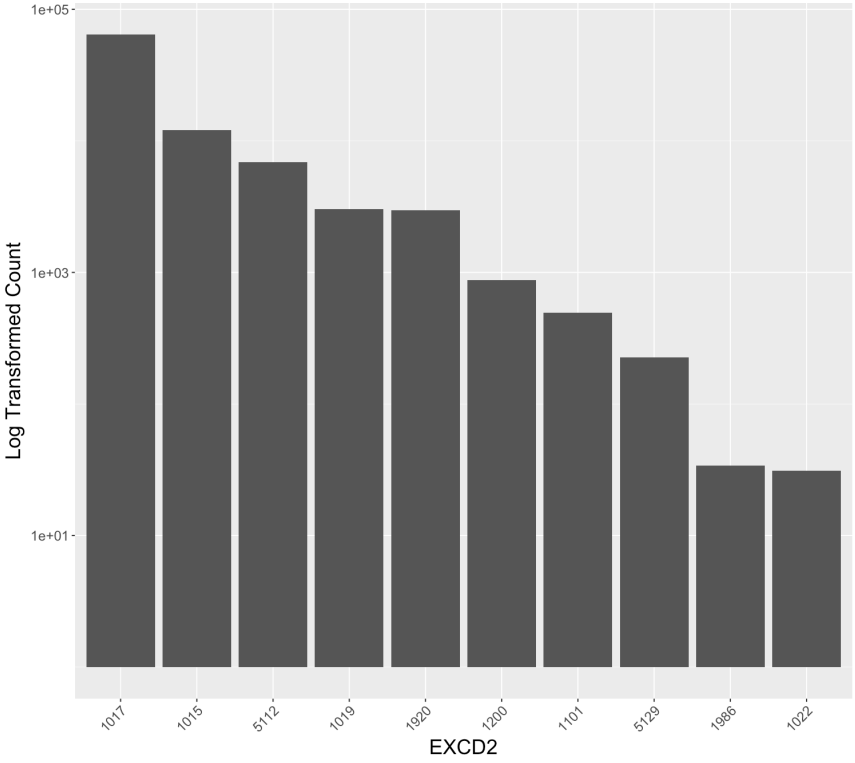
Field Name: EXCD2

Description:

EXCD2 is a categorical variable, possibly representing the code for the exempt reasons for EXLAND2 AND EXTOT2 records.

Unique Values:

EXTOT has 61 levels, taking 4-digit numbers from 1011 to 7160. There are 957,634 missing values exist. The top 10 most frequently occurred EXCD2 values are:



EXCD2	Percentage(%)
1017	70.6
1015	13.2
5112	7.6
1019	3.3
1920	3.3
1200	1.0
1101	0.5
5129	0.2
1986	0.0
1022	0.0

Field 28
Field Name: PERIOD

Description:
PERIOD is a categorical variable, indicating the change period of the record.

Unique Values:
All the records in this dataset take the value of “FINAL” in the PERIOD field.

Field 29
Field Name: YEAR

Description:
YEAR is a date variable, indicating the time that the record is made.

Unique Values:
All the records in this dataset take the value of “2010/11” in the YEAR field.

Field 30
Field Name: VALTYPE

Description:
VALTYPE is a categorical variable, indicating the valid type of the record.

Unique Values:
All the records in this dataset take the value of “AC-TR” in the VALTYPE field.