Fraud Analytics Report on NY Property Data

Team 2

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Executive Summary

In this project, we accepted a request from NY Property to help them detect anomalies in their NY property data records. NY Property Data represents NYC properties assessments for the purpose of calculating property tax, grant eligible properties, exemptions and/or abatements.

Because of the large scale of the dataset, we first examined the data quality and performed exploratory data analysis on some important fields to prepare for the algorithm development in the next step.

Based on the features of this dataset, we conducted feature engineering and dimensionality reduction to develop two unsupervised fraud detection algorithms – Heuristic Algorithm and Autoencoder Algorithm to detect unusual records.

By combining the ranking scores from these two algorithms, we suggested that the final unusual records that have the biggest possibility to be a fraud record should be 10 records which rank top 10 in the final ranking score. Unreasonable full value and lot area are some features of these unusual records.

For future analysis of these unusual records, we suggested NYC properties to conduct further research into whether the abnormalities could have a reasonable explanation because of special property categories such as government building, public park, etc.

Table of Contents

I Description of Data

1. Data Description

Dataset Name: NY property data / Property Valuation and Assessment Data

Data source: NYC Open Data Website- https://data.cityofnewyork.us/Housing-Development/Property-Valuation-and-Assessment-Data/rgy2-tti8

Time period: 2010/11

Number of columns: 32

Number of records: 1,070,994

2. Data Summary

2.1 Categorical Variables

Field Names	Records that have values	% populated	# of unique values	Most common field value
RECORD	1,070,994	100.0	1,070,994	NA
BBLE	1,070,994	100.0	1,066,541	NA
B	1,070,994	100.0	5	4
BLOCK	1,070,994	100.0	13,984	3944
LOT	1,070,994	100.0	6,366	1
EASEMENT	4636	0.4	13	E
TAXCLASS	1,070,994	100.0	11	1
EXT	354305	33.1	4	G
ZIP	1,041,104	97.2	197	10,314
EXMPTCL	15,579	1.5	15	X1
PERIOD	1,070,994	100.0	1	FINAL
YEAR	1,070,994	100.0	1	2010/11
VALTYPE	1,070,994	100.0	1	AC-TR

OWNER	1,039,249	97.0	863,348	PARKCHESTER PRESERVAT
BLDGCL	1,070,994	100.0	200	R4
STADDR	1,070,318	99.9	839,281	501 SURF AVENUE
EXCD1	638,488	59.6	130	1017.0
EXCD2	92,948	8.7	61	1017.0

2.2 Numeric Variables

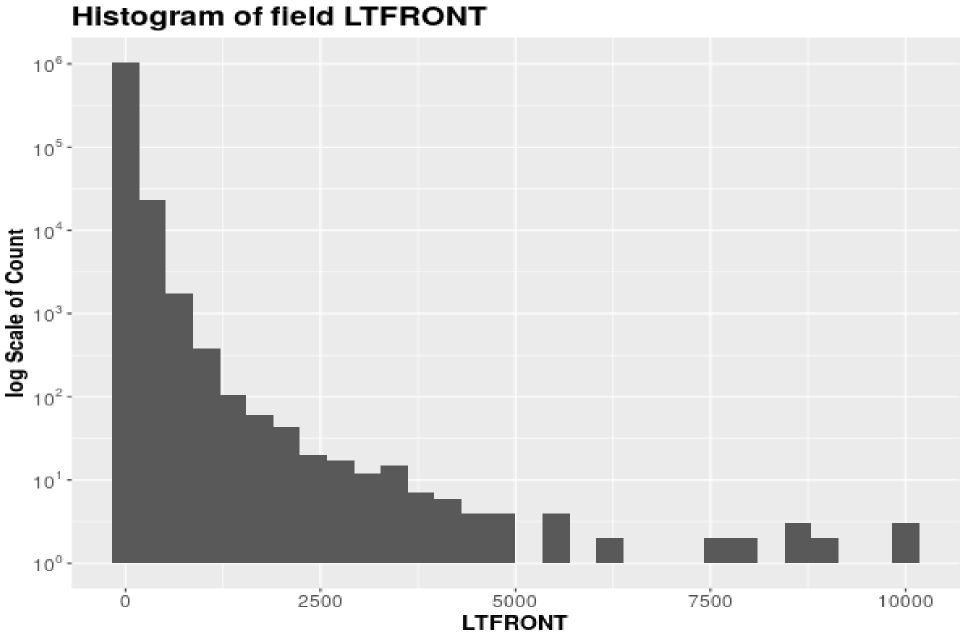
Field Name	# of records	% populated	#unique values	# records with value 0	Mean	Standard Deviation	Minimum	Maximum
LTFRONT	1,070,994	100.0	1,297	169,108	36.6	74.0	0	9,999
LTDEPTH	1,070,994	100.0	1,370	170,128	88.9	76.4	0	9,999
STORIES	1,014,730	94.7	112	0	5.0	8.4	1	119
FULLVAL	1,070,994	100.0	109,324	13,007	874,264.5	11,582,431	0	6,150,000,000
AVLAND	1,070,994	100.0	70,921	13,009	85,067.9	4,057,260	0	2,668,500,000
AVTOT	1,070,994	100.0	112,914	13,007	227,238.2	6,877,529.3	0	4,668,308,947
EXLAND	1,070,994	100.0	33,419	491,699	36,423.9	3,981,575.8	0	2,668,500,000
EXTOT	1,070,994	100.0	64,255	432,572	91,187.0	6,508,402.8	0	4,668,308,947
BLDFRONT	1,070,994	100.0	612	228,815	23.0	35.6	0	7,575
BLDDEPTH	1,070,994	100.0	621	228853	39.9	42.7	0	9,393
AVLAND2	282,726	26.4	58,593	0	246,235.7	6,178,962.6	3	2,371,005,000
AVTOT2	282,732	26.4	111,361	0	713,911,4	11,652,528.9	3	4,501,180,002
EXLAND2	87,449	8.2	22,196	0	351,235.7	10,802,212.7	1	2,371,005,000
EXTOT2	130,828	12.2	48,349	0	656,768.3	16,072,510.2	7	4,501,180,002

2.3 Histograms of important fields

Field 1

Field Name: LTFRONT

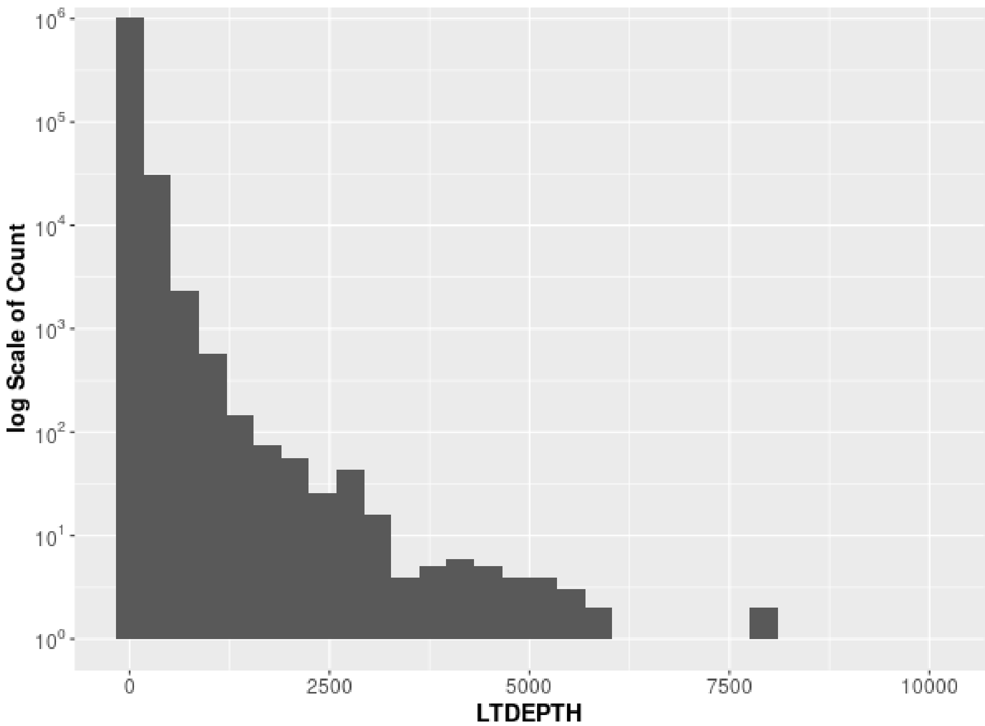
Description: Lot Frontage in feet.



Field 2

Field Name: LTDEPTH

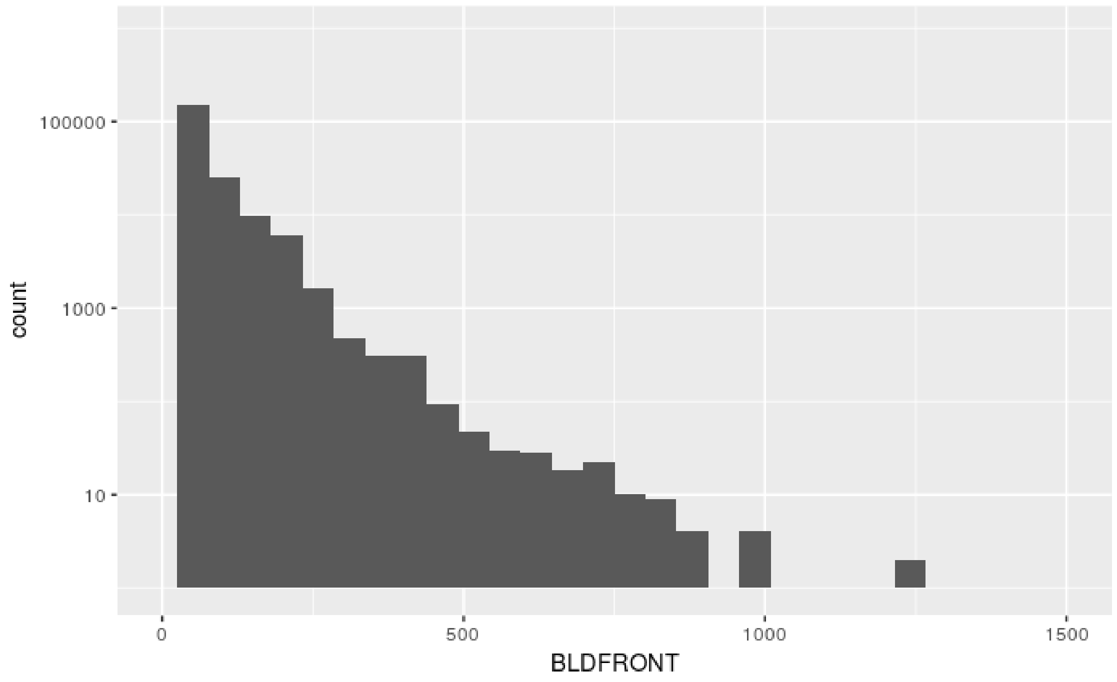
Description: Lot Depth in feet.



Field 3

Field Name: BLTFRONT

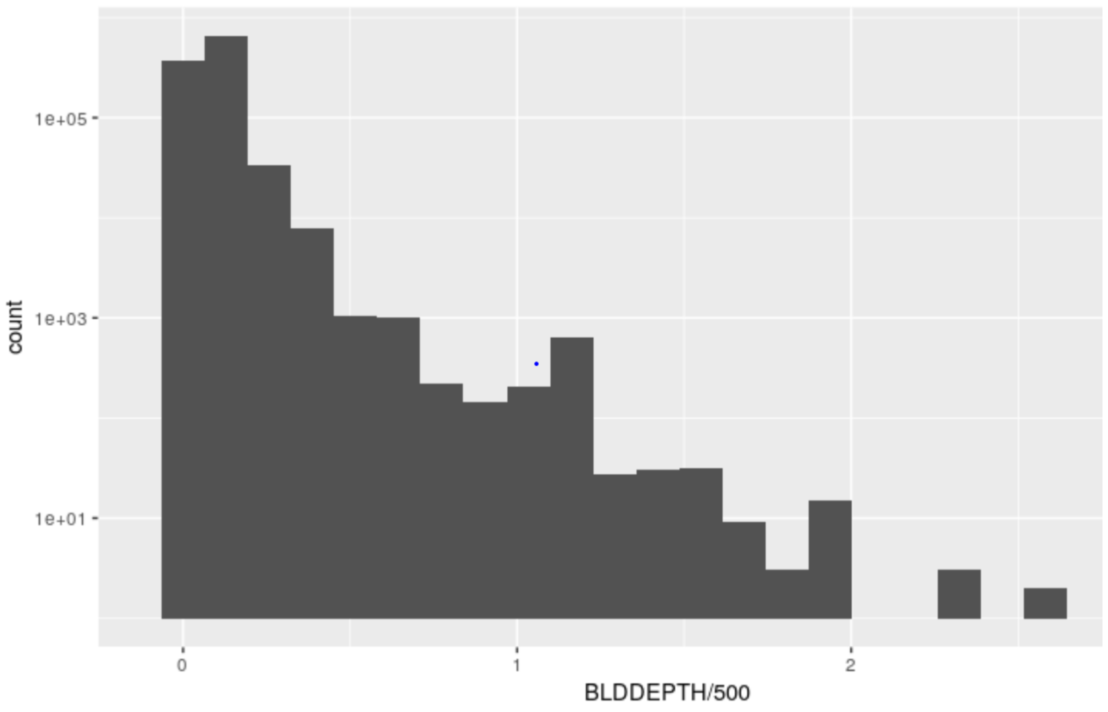
Description: Building Frontage in feet.



Field 4

Field Name: BLTDEPTH

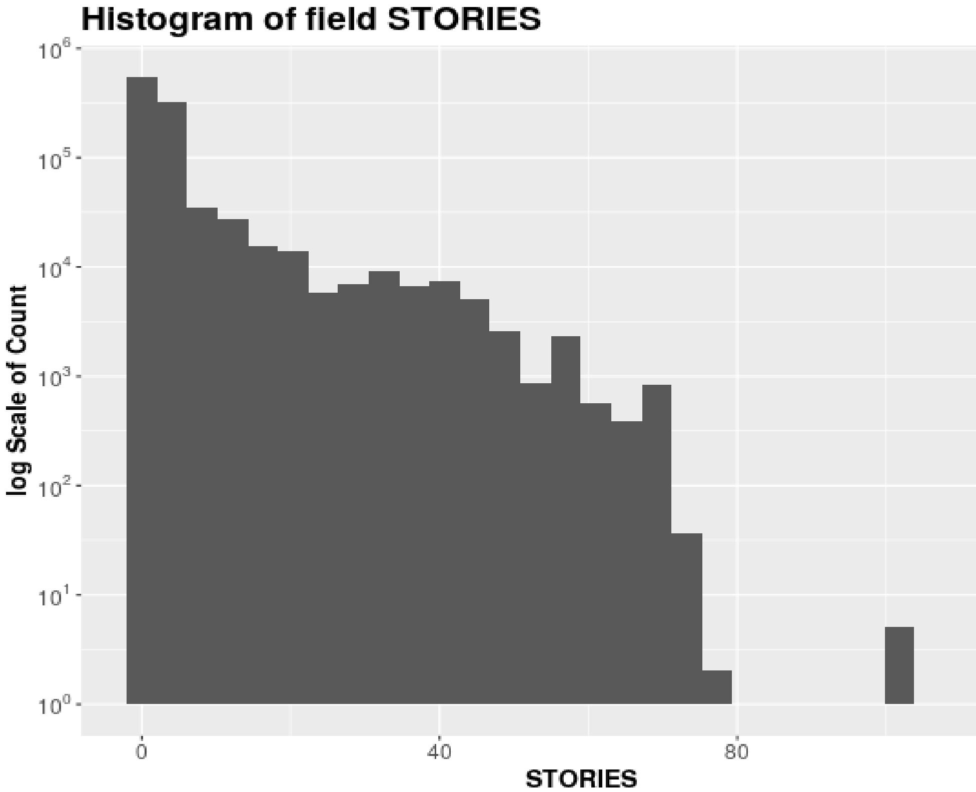
Description: Building Depth in feet.



Field 5

Field Name: STORIES

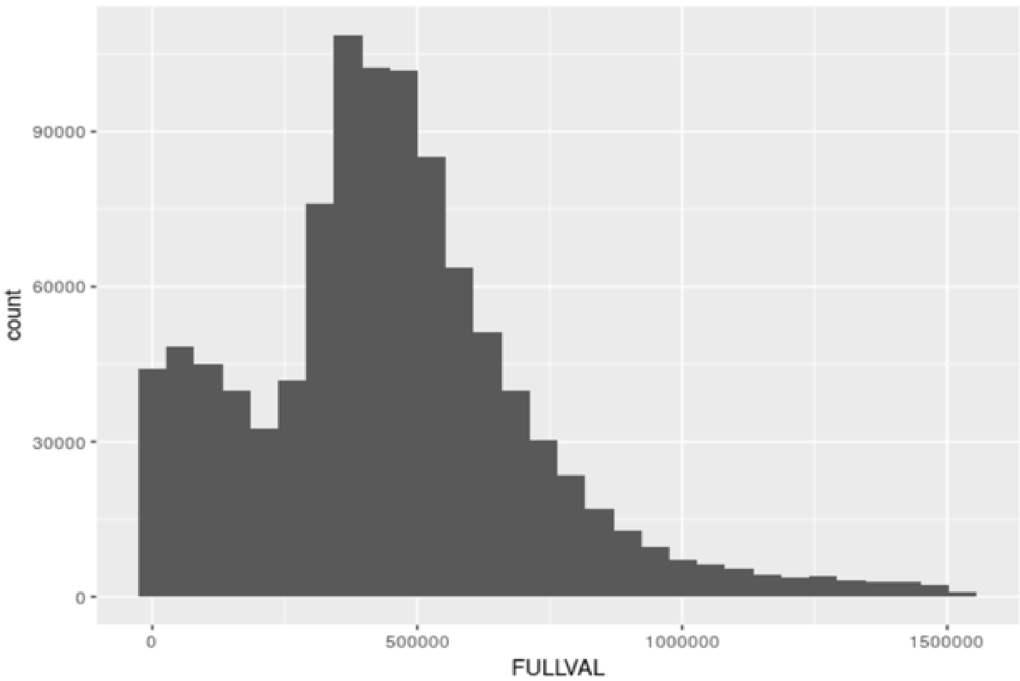
Description: The number of stories for the building (Number of Floors).



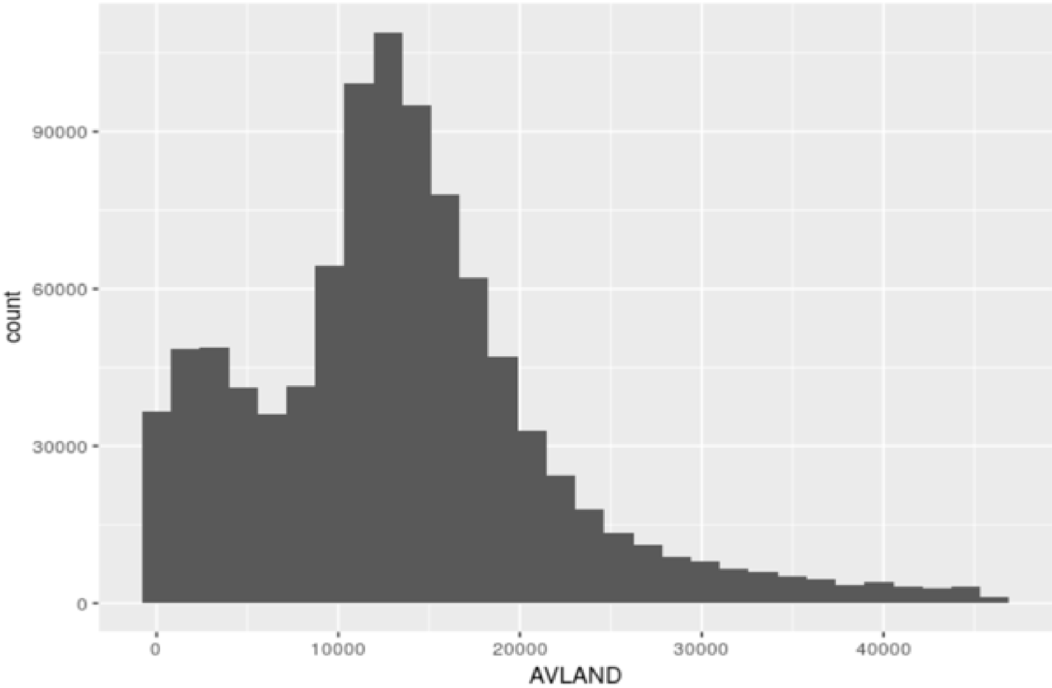
Field 6

Field Name: FULLVAL

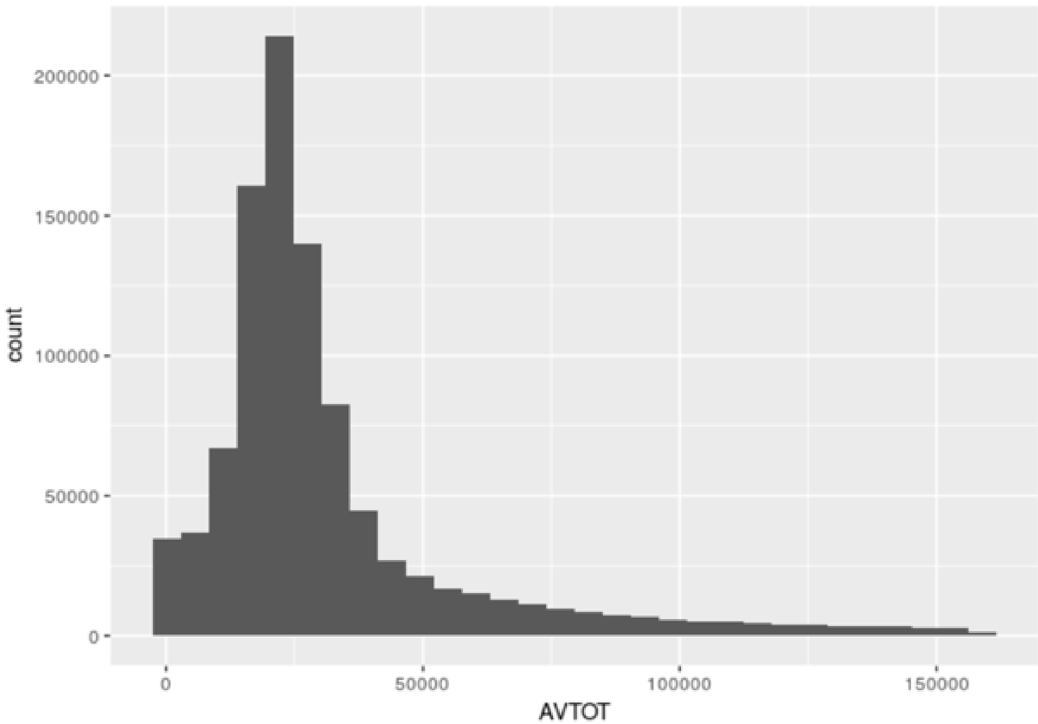
Description: If not zero, Current year's total market value of the property.



Field 7
Field Name: AVLAND
Description: Assessed land value.



Field 8
Field Name: AVTOT
Description: Assessed total value.



II Data Cleaning

In this dataset, there are many fields with missing values. We choose 9 fields that are important to algorithm building to fill in missing values.

Field 1

Name: ZIP

Method: Since the distribution of ZIP code in the original dataset has an obvious sequential characteristic, we could fill in a missing ZIP code with the previous one that is available. For example, if a ZIP is missing and the previous ZIP is 11208, we can simply replace the missing value with 11208.

Field 2

Name: STORIES

Method: After checking the original dataset, we noticed that properties at the same street address, in most cases, have the same number of stories. Therefore, we could fill in a missing stories value with the number of stories that a property has at the same street (STADDR) However, if the number of stories at a certain street is also unknown, we could group by ZIP and BLDGCL, then fill in the missing value with the average number of stories in that ZIP code.

Field 3 ~ 5

Name: FULLVAL, AVLAND, AVTOT

Method: For FULLVAL, AVLAND and AVTOT, since the distributions for the three fields are quite condensed with only a few outliers, hence we could aggregate by ZIP and TAXCLASS and fill in a missing value with the median of that group. If the group size is smaller than 5, we could merely aggregate by TAXCLASS.

Field 6 ~ 9

Name: LTFRONT, LTDEPTH, BLDFRONT, BLDDEPTH

Method: For these four fields that are highly correlated with LOT and B (Borough), we could aggregate by LOT and B, and then fill in a missing value with the median of that group. We choose medians in order to minimize the effects of outliers on the projected values. If there are still missing values after filling in the field with group medians, we can continue filling the rest of missing values with group medians gained from aggregating only by B.

III Variable Creation

1. Critical Variables Selection

First, we select the following variables from our original dataset

V_1= FULLVAL V_2 = AVLAND V_3 = AVTOT

2. Variables Group by and Creation

Then, we created 3 new variables S1, S2, S3. S1 represents the area of lot, S2 represents the one story area of a building, S3 represents the total area of a building

S_1 = LTFRONT * LTDEPTH
S_2 = BLDFRONT * BLDDEPTH
S_3 = S_2* STORIES

For each record make 9 ratios:
r1, r4, r7 represents market value per lot, per one story area, per total story area
r2, r5, r8 represents land area per lot area, per one story area, per total story area
r3, r6, r9 represents units of building per lot, per one story area, per total story area

$$r_1 = \frac{V_1}{S_1} \qquad r_2 = \frac{V_1}{S_2} \qquad r_3 = \frac{V_1}{S_3}$$
$$r_4 = \frac{V_2}{S_1} \qquad r_5 = \frac{V_2}{S_2} \qquad r_6 = \frac{V_2}{S_3}$$
$$r_7 = \frac{V_3}{S_1} \qquad r_8 = \frac{V_3}{S_2} \qquad r_9 = \frac{V_3}{S_3}$$

Separately group records by the 5 groups: zip5, zip3, TAXCLASS, borough, all because r1-r9 might varies a lot in different area, tax class and borough.
For each group , calculate $< r_i >_g$, the average of each r_i for each group g
For each record calculate 45 variables:

$$\frac{r_1}{< r_1 >_g}, \quad \frac{r_2}{< r_2 >_g}, \quad \frac{r_3}{< r_3 >_g}, \quad \ldots \quad \frac{r_9}{< r_9 >_g} \quad g= 1, \ldots, 5$$

The following table shows the list of all 45 variables we created.

Variable Name	Formula	Variable Name	Formula	Variable	Formula
val_lft_zip5	r1/<r1>1	land_ltf_zip5	r4/<r4>1	tol_lft_zip5	r7/<r7>1
val_lft_zip3	r1/<r1>2	land_ltf_zip3	r4/<r4>2	tol_lft_zip3	r7/<r7>2
val_lft__taxclass	r1/<r1>3	land_ltf_taxclass	r4/<r4>3	tol_lft_taxclass	r7/<r7>3
val_lft__borough	r1/<r1>4	land_ltf_borough	r4/<r4>4	tol_lft_borough	r7/<r7>4
val_lft__all	r1/<r1>5	land_ltf_all	r4/<r4>5	tol_lft_all	r7/<r7>5
val_bld_zip5	r2/<r2>1	land_bld_zip5	r5/<r5>1	tol_bld_zip5	r8/<r8>1
val_bld_zip3	r2/<r2>2	land_bld_zip3	r5/<r5>2	tol_bld_zip3	r8/<r8>2
val_bld_taxclass	r2/<r2>3	land_bld_taxclass	r5/<r5>3	tol_bld_taxclass	r8/<r8>3
val_bld_borough	r2/<r2>4	land_bld_borough	r5/<r5>4	tol_bld_borough	r8/<r8>4
val_bld_all	r2/<r2>5	land_bld_all	r5/<r5>5	tol_bld_all	r8/<r8>5
val_store_zip5	r3/<r3>1	land_store_zip5	r6/<r6>1	tol_store_zip5	r9/<r9>1
val_store_zip3	r3/<r3>2	land_store_zip3	r6/<r6>2	tol_store_zip3	r9/<r9>2
val_store_taxclass	r3/<r3>3	land_store_taxclass	r6/<r6>3	tol_store_taxclass	r9/<r9>3
val_store_borough	r3/<r3>4	land_store_borough	r6/<r6>4	tol_store_borough	r9/<r9>4
val_store_all	r3/<r3>5	land_store_all	r6/<r6>5	tol_store_all	r9/<r9>5

IV Algorithms

1. Heuristic Algorithm

Before performing PCA, the variables are first z-scaled so that the principal components are not dominated by variables of a much larger scale.

After performing PCA, top 5 principal components were selected to cover 93% of the total variance. Summary results are shown below.

```
Importance of first k=5 (out of 45) components:
                          PC1    PC2     PC3    PC4     PC5
Standard deviation     5.2040 2.8861 1.91884 1.2781 1.09150
Proportion of Variance 0.6018 0.1851 0.08182 0.0363 0.02648
Cumulative Proportion  0.6018 0.7869 0.86874 0.9050 0.93152
```

After that, the original data was represented in the chosen principal components and the 5 PCs were further z-scaled to be on the same footing scale.

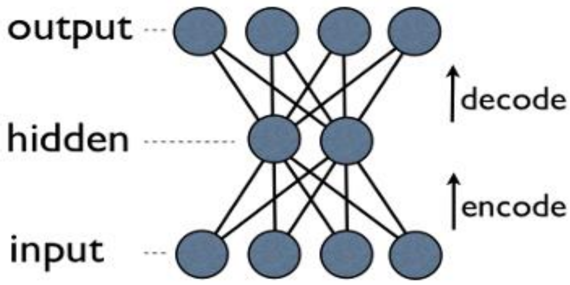
A summary table of minimum, maximum of variables and Euclidean distance were calculated. The records were then arranged with descending order of Euclidean distance and assigned a unique rank number.

For a dataset with many variables, there is a high probability of hidden correlations between variables, PCA could decorrelate the input data. In addition, with such high dimensions, the analysis could be slow and inefficient, PCA captures the most important components without losing much information, thus it is a much more efficient way of analysis.

2. Autoencoding

● How does an autoencoder work?

An autoencoder is a neural network that is trained by unsupervised learning, which is trained to learn reconstructions that are close to its original input. An autoencoder is composed of two parts, an encoder, and a decoder. A neural network with a single hidden layer has an encoder and decoder respectively. There are also weights, transformation function, and bias. The encoder maps an input vector to a hidden representation by an affine mapping following a nonlinearity. The decoder maps the hidden representation back to the original input space as reconstruction by the same transformation as the encoder.



In short, this is training the autoencoder to reproduce the original input x from a noisy input ˆ x. This allows the autoencoder to be robust to data with white noise and capture only meaningful patterns of the data. It uses the reconstruction error as the anomaly score. Data points with high reconstruction are anomalies. After training, the autoencoder will reconstruct normal data very well, while failing to do so with anomaly data which the autoencoder has not encountered.

● Reasons for using Autoencoder:

1. Autoencoder is a deep learning model, which can conduct unsupervised learning and produce features in the dataset. This method utilizes deep learning to provide a better method than purely scaling as an autoencoder can study more about different features.

2. The record prediction is more accurate than a normal machine learning model. Also, this is a model using its own records to predict itself, so autoencoder is able to conduct unsupervised learning, unlike the other neural network models.

3. It may be more efficient, in terms of model parameters, to learn several layers with an autoencoder rather than to learn one huge transformation with PCA.

4. An autoencoder can learn non-linear transformations, unlike PCA, with a non-linear activation function and multiple layers.

- **Autoencoder Calculation:**

After z-scaling the cleaned data and conducting Principal Component Analysis, the dataset is z-scaled again to get our final data for autoencoder model. Then, there is an R package called h2o which has an autoencoder deep learning function that allows us to reconstruct the PCA datasets we produced before and study the features to reproduce the same records. The Euclidean Distance between the actual values and the prediction values from autoencoder will be the fraud scores of each record for this case.

Autoencoder results (Top ten abnormal scores):

PCA1	PCA2	PCA3	PCA4	PCA5	Score	RECORD	RANK
835.6818	-130.911	419.6394	187.0608	-1.29663	1455.51433	565392	1
153.2996	-673.244	-451.05	-159.731	-185.295	955.572566	1067360	2
374.6287	476.2997	-737.942	357.88	45.35209	774.638242	632816	3
205.6739	105.1439	125.7514	-80.3834	-584.228	694.721653	917942	4
135.5034	121.3464	-38.0273	-340.176	234.3469	379.324027	85886	5
61.50492	-144.653	35.10579	130.6117	275.0408	363.198204	556609	6
64.30577	-196.766	-17.4422	107.63	180.939	350.003329	821853	7
53.18943	-156.76	2.742903	115.5123	199.3594	318.413126	776306	8
73.60326	-112.862	23.70273	38.04658	276.9273	317.37586	912501	9
32.76957	-172.626	-154.257	-94.635	-119.006	307.991139	770594	10

3. Score Combination

Combine scores from both of the Algorithms:

After we got the z-score and autoencoder score, we sorted those two scores ascendingly and replaced each score with the rank order. Then each score was on the same footing and could be combined. We calculated the average of the two ranking orders and took it as our final score for each record. From the result table, the smaller the score is, the higher the chance the record is anomalous.

V Results

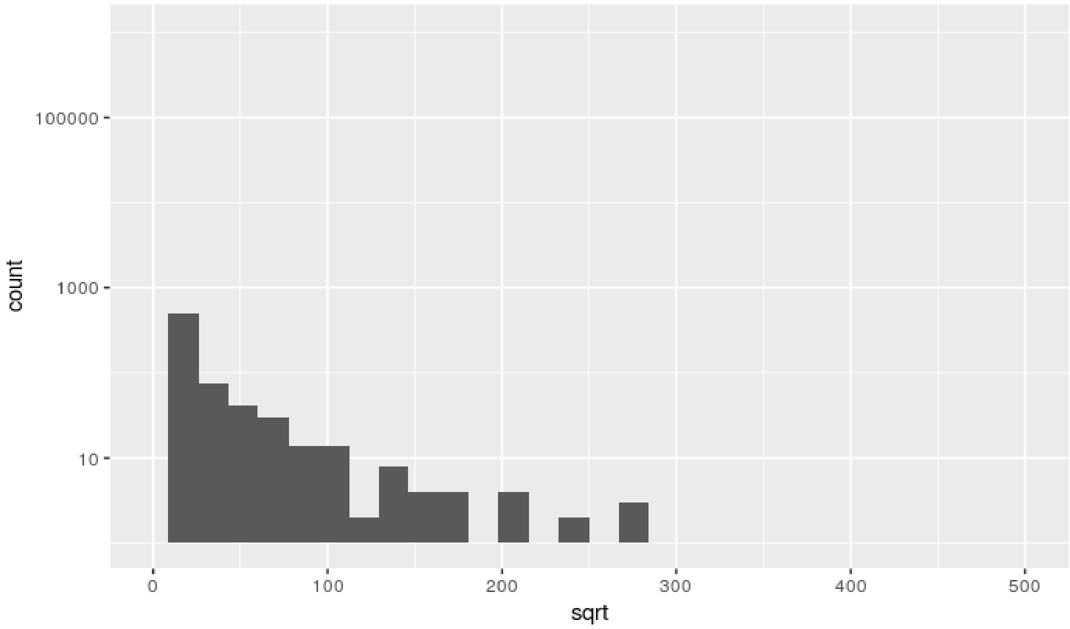
By using two algorithms and combine scores from each algorithm, finally we got the list of unusual records, and we chose the top 10 unusual records as our examination object. The following table shows the top 10 unusual records with scores from the heuristic algorithm, autoencoding and combination of two ranking scores.

Final results based on two ranking scores:

RECORD	Rank 1	Rank 2	Final Score
565392	2	1	**1.5**
632816	1	3	**2.0**
1067360	3	2	**2.5**
917942	4	4	**4.0**
85886	5	5	**5.0**
556609	6	6	**6.0**
821853	8	7	**7.5**
912501	7	9	**8.0**
776306	9	8	**8.5**
770594	10	10	**10.0**

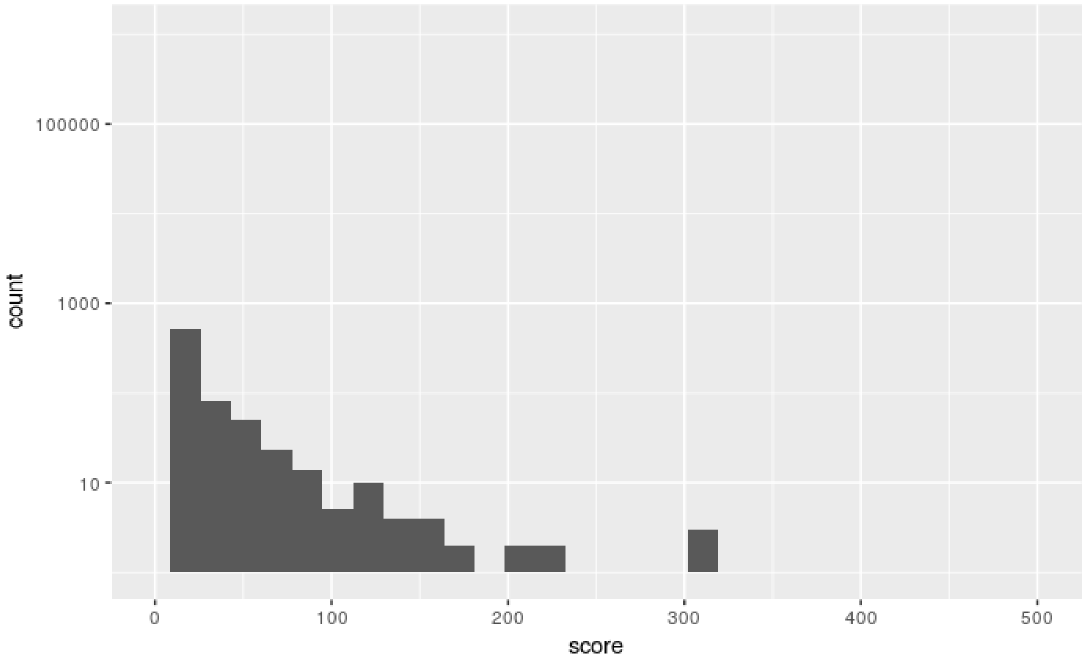
Heuristic Algorithm Result:

The following chart shows the distribution of scores from heuristic algorithm. We can see that the distribution is right-skewed.



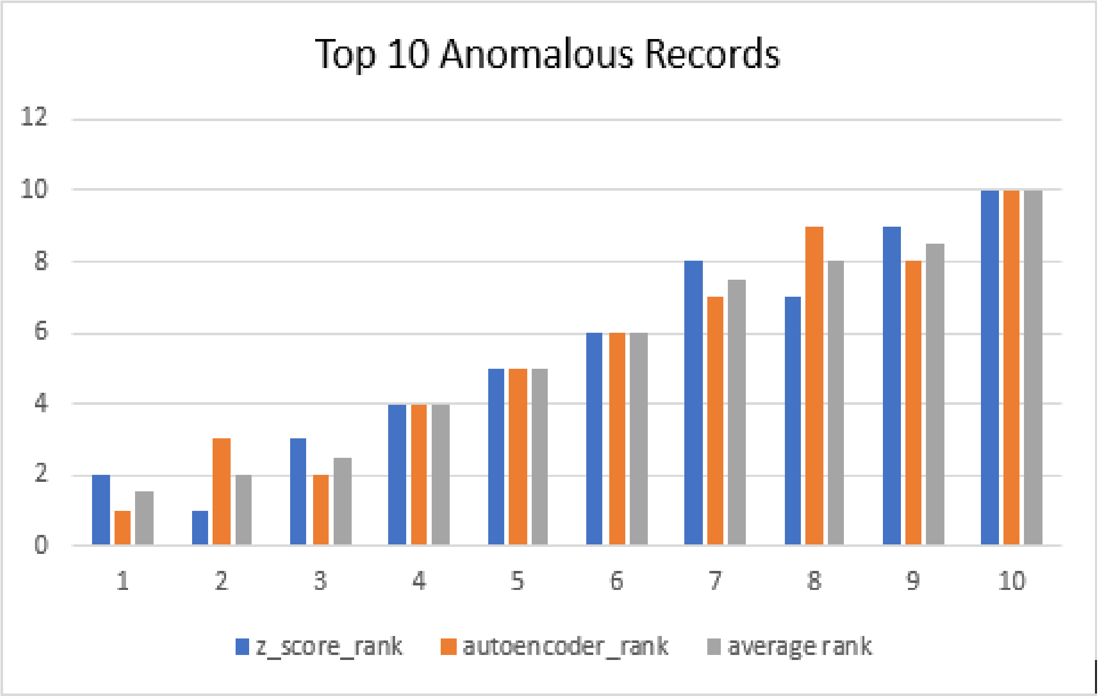
Autoencoder Algorithm Result:

The following chart shows the distribution of scores from the autoencoder algorithm. We can see the distribution is also right-skewed.



Combination Result:

The following chart shows the comparison of rank among heuristic algorithm rank, autoencoder algorithm rank, and final average rank. We can find that the outcome of the two algorithms are pretty similar so we decide to use average rank as our final score.



Interpretation from the result:

In the following paragraphs, we use some tables to describe the reason why these top10 records are unusual.

1. Record: 565392

For record 565392, there are three similar properties among the whole data set based on ZIP, B, BLOCK, TAXCLASS and LOT size. By comparing them, we can find that the full value, average land value and average total value of Record 565392 are much higher (about 100-1000 times) than the other similar properties.

RECORD	B	BLOCK	TAXCLASS	LTFRONT	LTDEPTH	FULLVAL	AVLAND	AVTOT	ZIP
565392	**3**	**8590**	**4**	**117**	**108**	**4,326,303,700**	**1,946,836,665**	**1,946,836,665**	**11229**
565393	3	8590	4	324	252	41,615,000	18,096,750	18,726,750	11229
565394	3	8590	4	155	150	2,740,000	1,138,500	1,233,000	11229
565399	3	8591	4	200	170	1,521,450	684,653	684,653	11229

2. Record: 632816

Record 632816 has BLDFRONT and BLDDEPTH values of 1 which seems unusual. In addition, compared to records with same B, TAXCLASS, ZIP and BLDGCL, it has significantly higher values (e.g. FULLVAL, AVLAND, AVTOT).

RECORD	BLOCK	LOT	LTFRONT	LTDEPTH	FULLVAL	AVLAND	AVTOT	BLDFRONT	BLDDEPTH
632816	**1,842**	**1**	**157**	**95**	**2,930,000**	**1,318,500**	**1,318,500**	**1**	**1**
624591	1,559	6	34	90	1,240,000	558,000	558,000	0	0
625256	1,584	10	50	193	994,000	82,350	447,300	50	74
657545	2,870	1	50	100	1,250,000	54,450	562,500	44	36

3. Record: 1067360

For record 1067360, we found the 4 most similar records based on ZIP, STORIES, TAXCLASS and BLDGCL. As you can see from the following table, the abnormality of this record falls in the LTFRONT and LTDEPTH that are only 1 foot long for each value. As the LTFRONT and LTDEPTH represent the area of the lot, they seem abnormally small compared to other similar records buildings, which indicates the possibility of it being a fraudulent evaluation.

ZIP	BLDGCL	RECORD	LTFRONT	LTDEPTH	STORIES	FULLVAL	TAXCLASS	AVLAND
10307	**B2**	**1067360**	**1**	**1**	**2**	**836000**	**1**	**28800**
10307	B2	1066709	40	100	2	674000	1	23400
10307	B2	1067202	40	134	2	890000	1	28426
10307	B2	1068681	62	100	2	792000	1	23307
10307	B2	1069170	51	97	2	651000	1	19967

4. Record: 917942

By using the same B, BLOCK, BLDGCL, TAXCLASS to filter records, we got 3 similar records. From the following table, we found that the abnormality of Record 917942 is that FULLVAL, AVLAND, EXLAND and EXTOT are unusually larger than the other similar records.

RECORD	LTFRONT	LTDEPTH	STORIES	FULLVAL	AVLAND	EXLAND	EXTOT
917942	**4910**	**100**	**3**	**374,019,883**	**1,792,808,947**	**1,792,808,947**	**4,668,308,947**
917943	1500	3000	3	107,113,000	48,150,000	48,150,000	48,200,850
917948	6500	2600	1	150,000,000	67,500,000	67,500,000	67,500,000

5. Record: 85886

For record 85886, comparing records with same B, TAXCLASS, BLDGEL and similar range of LTFRONT and LTDEPTH values, it has BLDFRONT and BLDDEPT values of 8 which is unusual.

RECORD	LTFRONT	LTDEPTH	FULLVAL	AVLAND	EXLAND	BLDFRONT	BLDDEPTH
85,886	**4,000**	**150**	**70,214,000**	**31,455,000**	**31,455,000**	**8**	**8**
127,334	4,000	4,500	173,000,000	66,600,000	66,600,000	0	0
131,603	3,490	500	46,968,000	20,925,000	20,925,000	14	34
137,654	3,459	349	49,100,000	20,745,000	20,745,000	40	35
127,322	3,000	4,000	151,000,000	13,950,000	13,950,000	0	0

6. Record: 556609

For record 556609, we found the 3 most similar records based on ZIP, STORIES, TAXCLASS and BLDGCL. As you can see from the following table, the abnormality of this record lies in the fact that the property has an unusually high FULLVAL with a relatively small LTFRONT and LTDEPTH, which indicates the possibility of it being a fraudulent evaluation.

RECORD	LTFRONT	LTDEPTH	STORIES	FULLVAL	AVLAND	EXLAND	EXTOT
556609	**35**	**50**	**1**	**136,000,000**	**60,750,000**	**60,750,000**	**61,200,000**
542090	201	299	1	1,940,000	648,000	648,000	873,000
548427	200	500	1	3,140,000	1,264,500	1,264,500	1,413,000
550360	179	200	1	1,042,800	448,200	448,200	469,260

7. Record: 821853

For record 821853, there are four similar properties among the whole data set based on ZIP, B, BLDGCL, TAXCLASS and FULLVAL. By comparing them, we can find that the LTFRONT and LTDEPTH of Record 821853 are abnormally smaller than the other similar properties.

RECORD	B	BLDGCL	TAXCLASS	LTFRONT	LTDEPTH	FULLVAL	ZIP
821853	**4**	**U7**	**3**	**2**	**1**	**138000**	**11432**
821712	4	U7	3	100	30	138000	11432
821754	4	U7	3	200	60	138000	11432
821845	4	U7	3	294	50	138000	11432
821855	4	U7	3	272	50	138000	11432

8. Record: 912501

For record 912501, there are three similar properties among the whole data set based on ZIP, B, BLDGCL, TAXCLASS and LOT size. By comparing them, we can find that the full value, average land value and average total value of this property are much higher (about 10 times) than the other similar properties with bigger lot size.

RECORD	B	BLOCK	TAXCLASS	LTFRONT	LTDEPTH	FULLVAL	AVLAND	AVTOT	ZIP
912501	**4**	**13791**	**4**	**25**	**100**	**128,222,000**	**57,600,000**	**57,699,900**	**11413**
912502	4	13791	4	352	635	12,100,000	1,777,500	5,445,000	11413
912503	4	13791	4	315	700	13,500,000	2,047,500	6,075,000	11413
912504	4	13791	4	435	670	28,400,000	2,979,000	12,780,000	11413
912505	4	13791	4	516	771	17,800,000	2,250,000	8,010,000	11413

9. Record: 776306

By using the same B, BLDGCL, STORIES to filter records, we got 35 similar records. From the following table, we found that the abnormality of Record 776306 is that LTFRONT and LTDEPTH of this record are extremely small but the FULLVAL is unreasonably large.

RECORD	LTFRONT	LTDEPTH	STORIES	FULLVAL	AVLAND	EXLAND	EXTOT
776306	**6**	**1**	**1**	**524,500**	**95,625**	**0**	**0**
803290	93	49	1	432,000	19,440	0	0
803873	45	26	1	13,000	5,850	0	0
876767	31	143	1	26,300	11,835	11,835	11,835
820414	98	66	1	74,000	33,300	0	0

10. Record: 770594

By filtering records based the same B, TAXCLASS, ZIP, BLDGCL, Block we got 327 similar records. From the following table, we found that the abnormality of Record 770594 is that BLDFRONT and BLDDEPTH of record 770594 is much higher than other similar records.

RECORD	B	ZIP	TAXCALSS	BLDGCL	BLOCK	BLDFRONT	BLDDEPTH
770594	**4**	**111364**	**1A**	**R3**	**7621**	**96**	**60**
770450	4	111364	1A	R3	7621	0	0
770451	4	111364	1A	R3	7621	0	0
770452	4	111364	1A	R3	7621	0	0

VI Conclusion

In summary, we first performed exploratory data analysis on the dataset to have a general understanding of the data. After that, we filled empty cells with values we believe to be reasonable, which means they should have minimum impact on the analysis in the later part.

Before building any fraud model, we created 45 new variables which were derived from the variables available.

Two fraud models were used in this project, Principal Component Analysis and Autoencoding. The results were arranged in descending order based on the outlier scores, and then each record was given a unique ranking score, the most unusual record will have a ranking score of 1. These two fraud model produced a very similar result in terms of top 10 unusual records. The final score is an average of the 2 scores produced.

In the end, the top 10 records were examined individually and compared with records with similar features, such as B, TAXCLASS, and ZIP, to determine why these records were marked as outliers by the models.

Further steps like gathering additional information from other sources for these records could be done to examine if these unusual records are reasonable. For example, record 85886 has a pretty large LTFRONT and LTDEPTH but a very small BLDFRONT and BLDDEPTH, thus was marked as usual by the model. However, this property belongs to PARKS AND RECREATION, thus it may be a large park with a small administrative office.

Appendix

Appendix 1 Data Quality Report

1. Data description

Dataset Name: NY property data / Property Valuation and Assessment Data
Data source: NYC Open Data Website- https://data.cityofnewyork.us/Housing-Development/Property-Valuation-and-Assessment-Data/rgy2-tti8
Time period: 2010/11
Number of columns: 32
Number of records: 1,070,994

2. Summary

2.1 Numeric Values Table

Field Name	# of records	% populated	#Unique values	# Records with value 0	Mean	Standard Deviation	Minimum	Maximum
LTFRONT	1,070,994	100.0	1,297	169,108	36.6	74.0	0	9,999
LTDEPTH	1,070,994	100.0	1,370	170,128	88.9	76.4	0	9,999
STORIES	1,014,730	94.7	112	0	5.0	8.4	1	119
FULLVAL	1,070,994	100.0	109,324	13,007	874,264.5	11,582,431	0	6,150,000,000
AVLAND	1,070,994	100.0	70,921	13,009	85,067.9	4,057,260	0	2,668,500,000
AVTOT	1,070,994	100.0	112,914	13,007	227,238.2	6,877,529.3	0	4,668,308,947
EXLAND	1,070,994	100.0	33,419	491,699	36,423.9	3,981,575.8	0	2,668,500,000
EXTOT	1,070,994	100.0	64,255	432,572	91,187.0	6,508,402.8	0	4,668,308,947
BLDFRONT	1,070,994	100.0	612	228,815	23.0	35.6	0	7,575
BLDDEPTH	1,070,994	100.0	621	228853	39.9	42.7	0	9,393

AVLAND2	282,726	26.4	58,593	0	246,235.7	6,178,962.6	3	2,371,005,000
AVTOT2	282,732	26.4	111,361	0	713,911,4	11,652,528.9	3	4,501,180,002
EXLAND2	87,449	8.2	22,196	0	351,235.7	10,802,212.7	1	2,371,005,000
EXTOT2	130,828	12.2	48,349	0	656,768.3	16,072,510.2	7	4,501,180,002

2.2 Categorical Values Table

Field Names	Records that has values	% Populated	# of unique values	Most common field value
RECORD	1,070,994	100.0	1,070,994	NA
BBLE	1,070,994	100.0	1,066,541	NA
B	1,070,994	100.0	5	4
BLOCK	1,070,994	100.0	13,984	3944
LOT	1,070,994	100.0	6,366	1
EASEMENT	4636	0.4	13	E
TAXCLASS	1,070,994	100.0	11	1
EXT	354305	33.1	4	G
ZIP	1,041,104	97.2	197	10,314
EXMPTCL	15,579	1.5	15	X1
PERIOD	1,070,994	100.0	1	FINAL
YEAR	1,070,994	100.0	1	2010/11
VALTYPE	1,070,994	100.0	1	AC-TR
OWNER	1,039,249	97.0	863,348	PARKCHESTER PRESERVAT
BLDGCL	1,070,994	100.0	200	R4

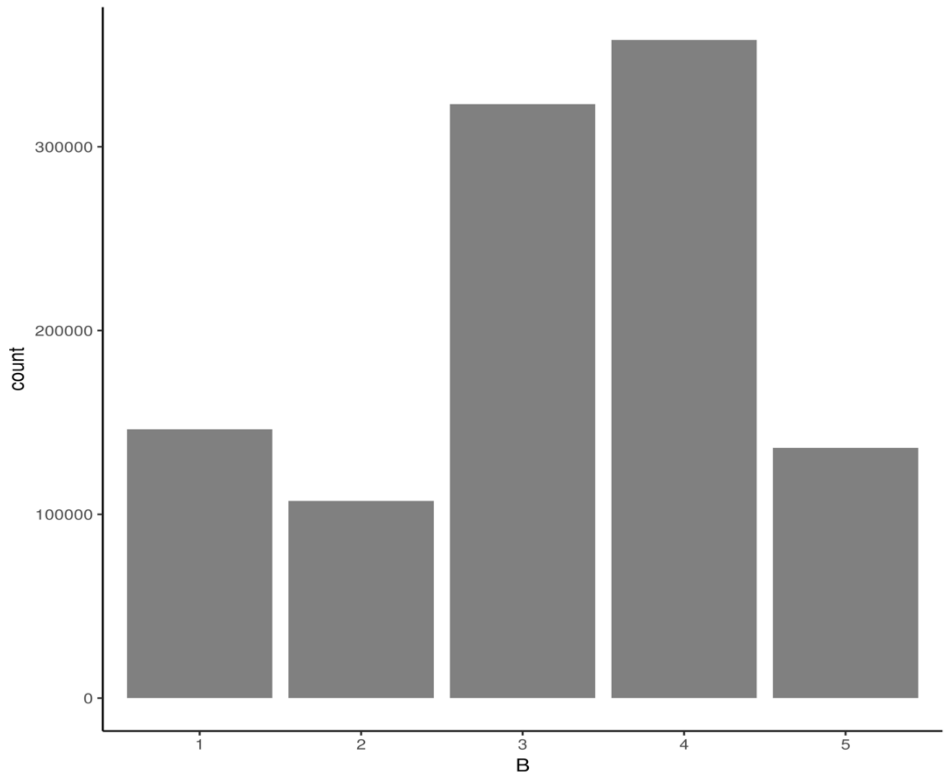
STADDR	1,070,318	99.9	839,281	501 SURF AVENUE
EXCD1	638,488	59.6	130	1017.0
EXCD2	92,948	8.7	61	1017.0

3. Data Field Exploration

Field 1
Field Name: RECORD
Description: Unique identifier of each data record. It is an integer from 1 to 1070994.

Field 2
Field Name: BBLE
Description: Concatenation of borough code, block code, Unique # within borough/block, easement. It is a 10-digit code.

Field 3
Field Name: B
Description: Borough codes.

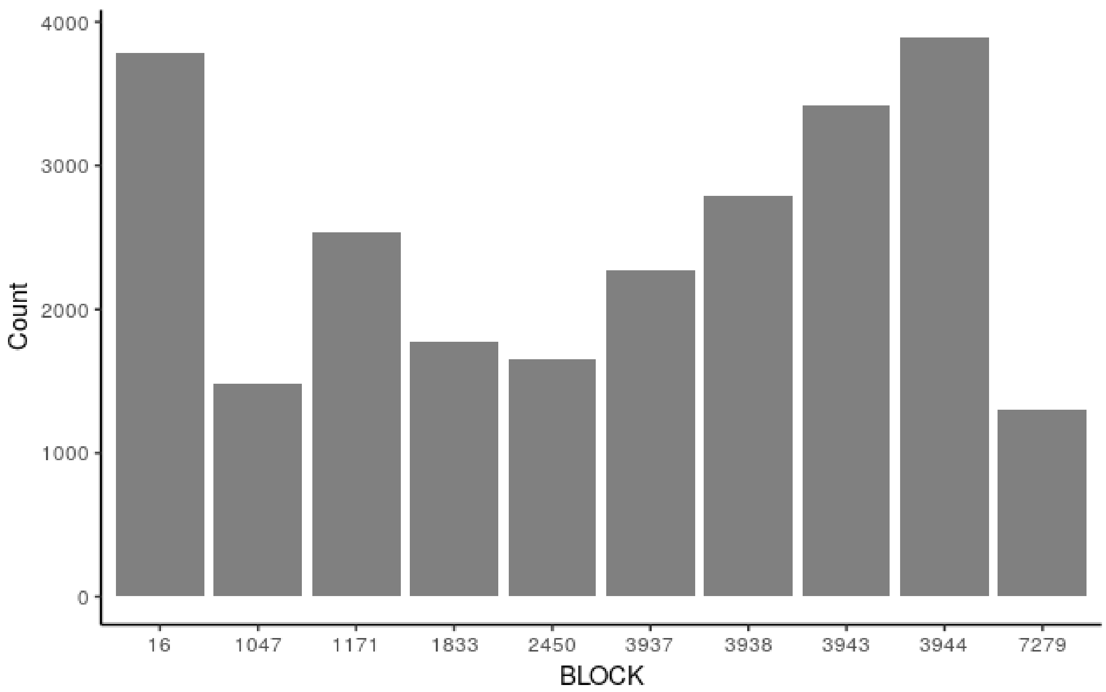


Field 4
Field Name: BLOCK
Description: Valid block ranges by borough.

Top10 Field Value

BLOCK	Count
3944	3,888
16	3,786
3943	3,424
3938	2,794
1171	2,535
3937	2,275
1833	1,774
2450	1,651
1047	1,480
7279	1,302

Top10 Field Value Plot

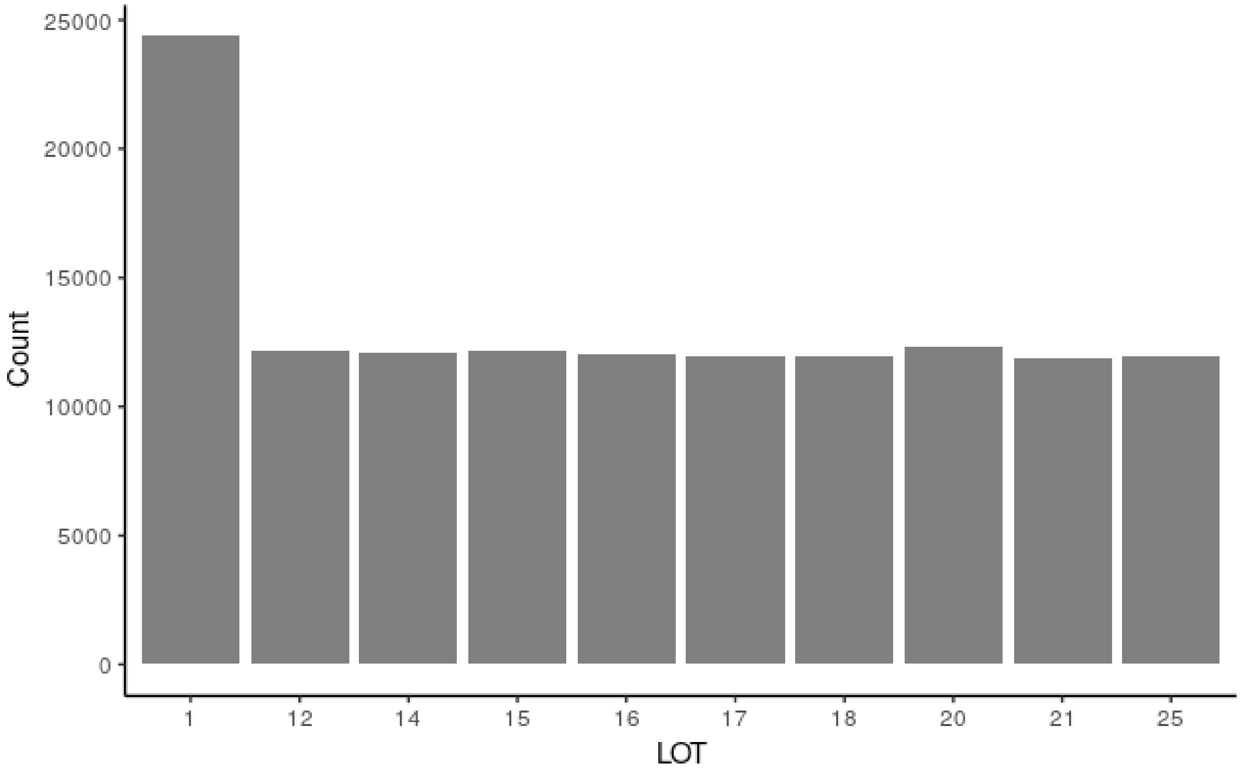


Field 5
Field Name: LOT
Description: Unique # within borough/block.

Top 10 Field Value

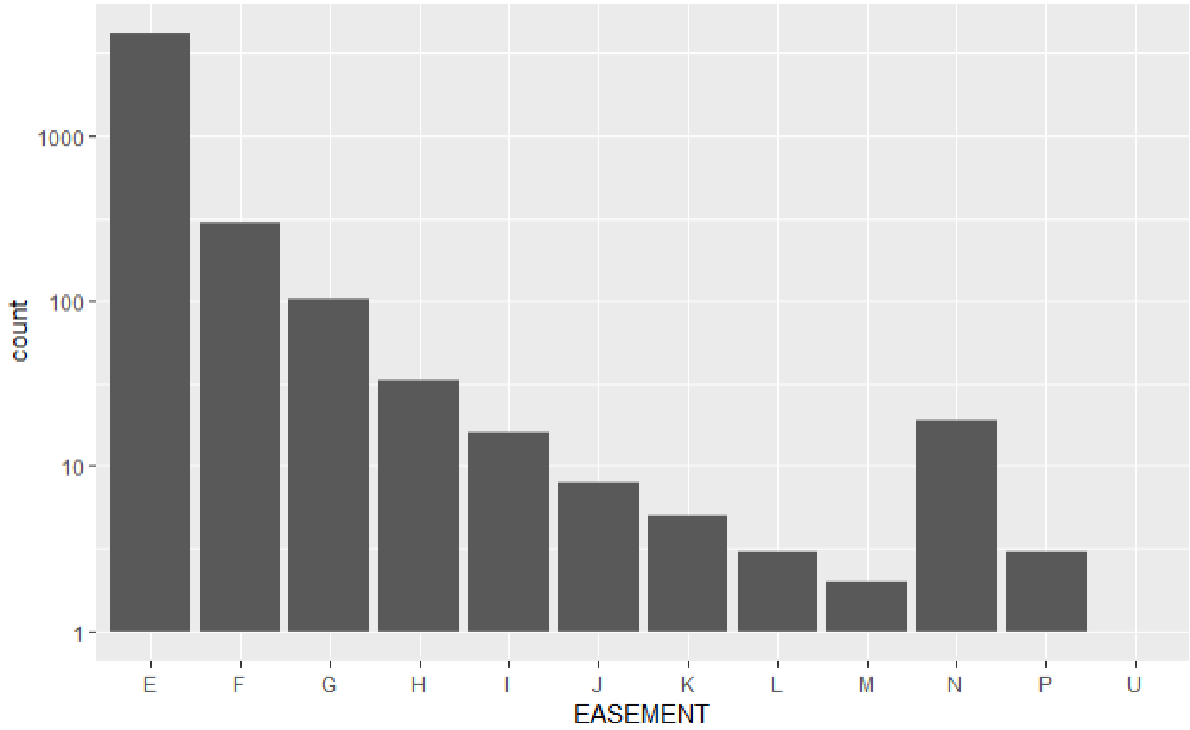
LOT	Count
1	24,367
20	12,294
15	12,171
12	12,143
14	12,074
16	12,042
17	11,982
18	11,979
25	11,949
21	11,840

Top10 Field Value Plot



Field 6
Field Name: EASEMENT
Description: Describe easement.

Plot the Easement Field on a Log Scale

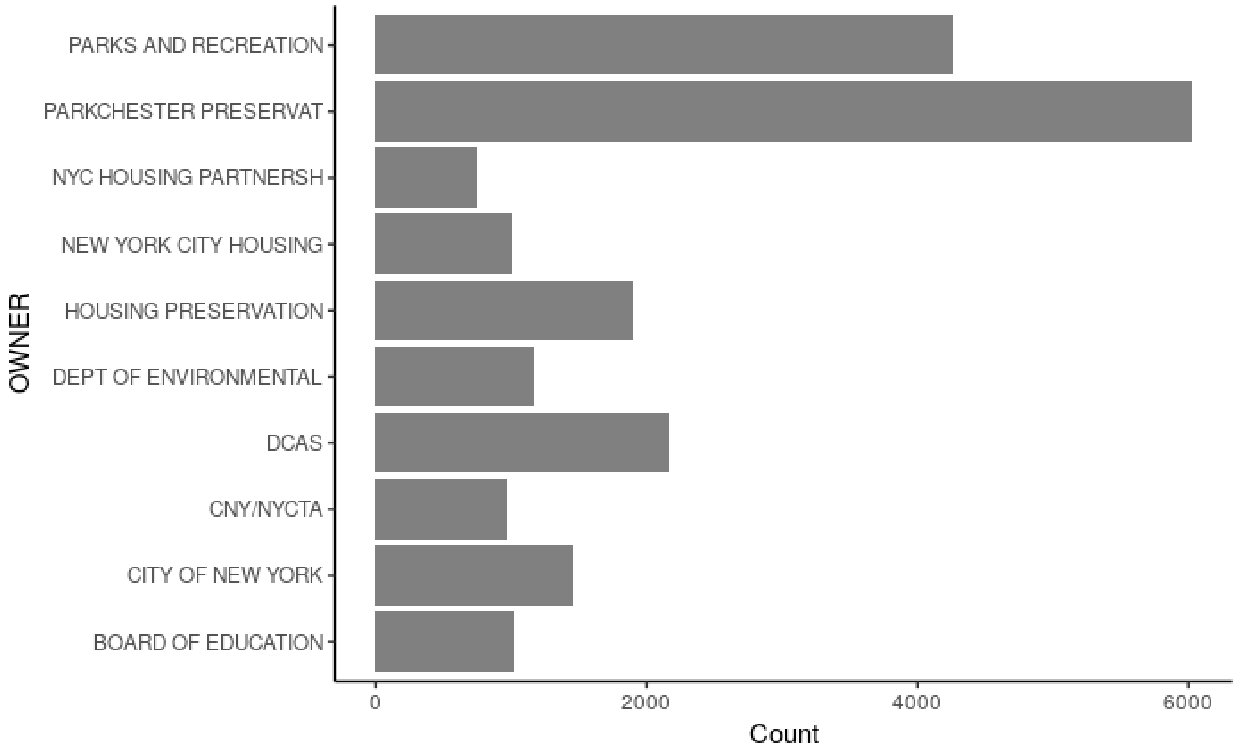


Field 7
Field Name: OWNER
Description: Owner's name.

Top 10 Field Value

OWNER	Count
PARKCHESTER PRESERVAT	6,021
PARKS AND RECREATION	4,255
DCAS	2,169
HOUSING PRESERVATION	1,904
CITY OF NEW YORK	1,450
DEPT OF ENVIRONMENTAL	1,166
BOARD OF EDUCATION	1,015
NEW YORK CITY HOUSING	1,014
CNY/NYCTA	975
NYC HOUSING PARTNERSH	747

Top10 Field Value Plot

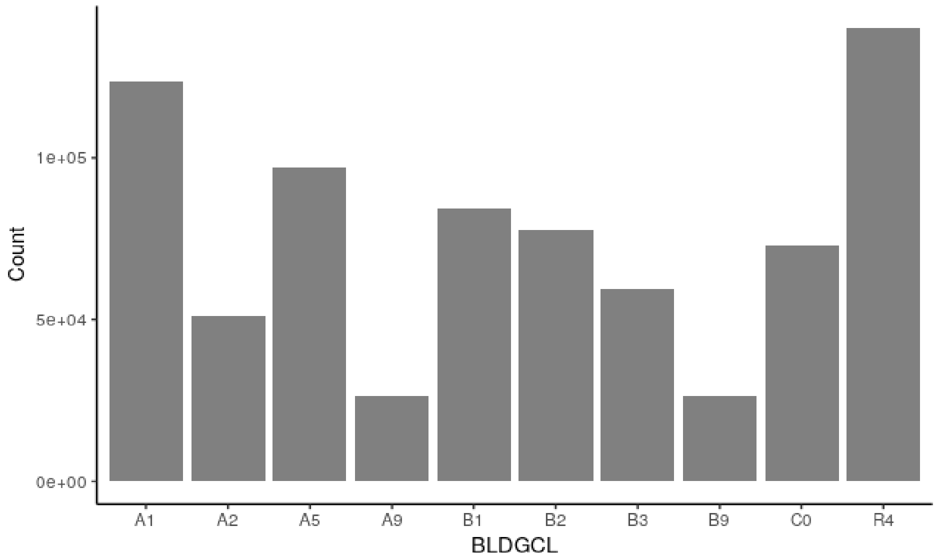


Field 8
Field Name: BLDGCL
Description: Building class.

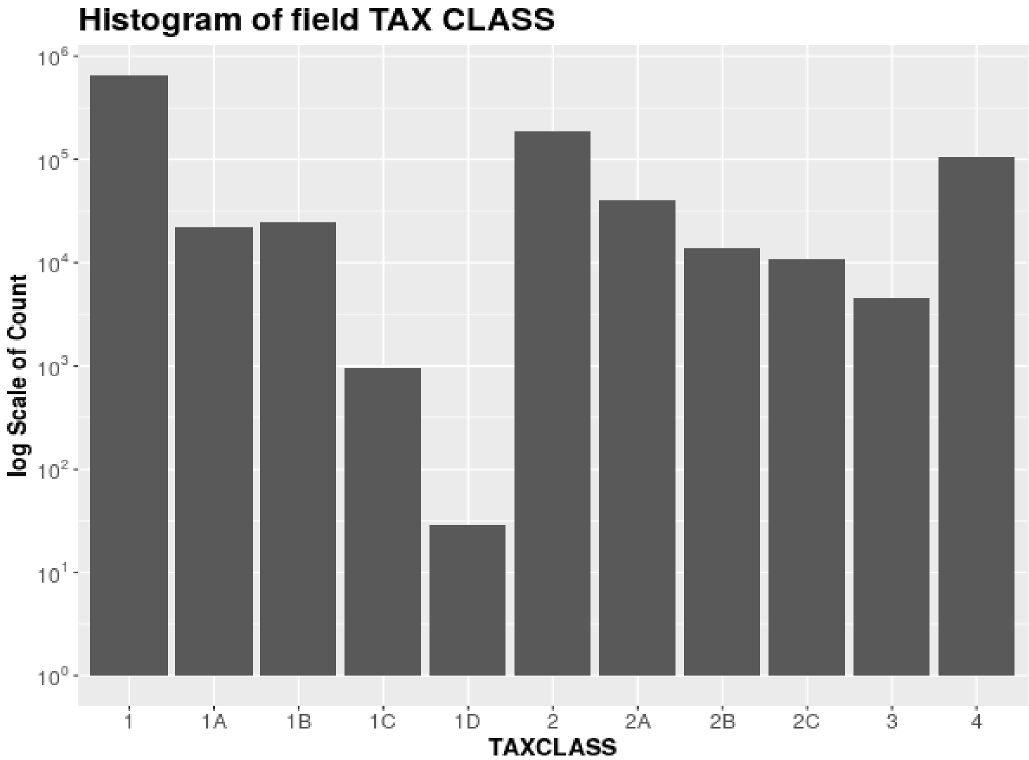
Top 10 Field Value

BLDGCL	Count
R4	139,879
A1	123,369
A5	96,984
B1	84,208
B2	77,598
C0	73,111
B3	59,240
A2	51,130
A9	26,177
B9	26,133

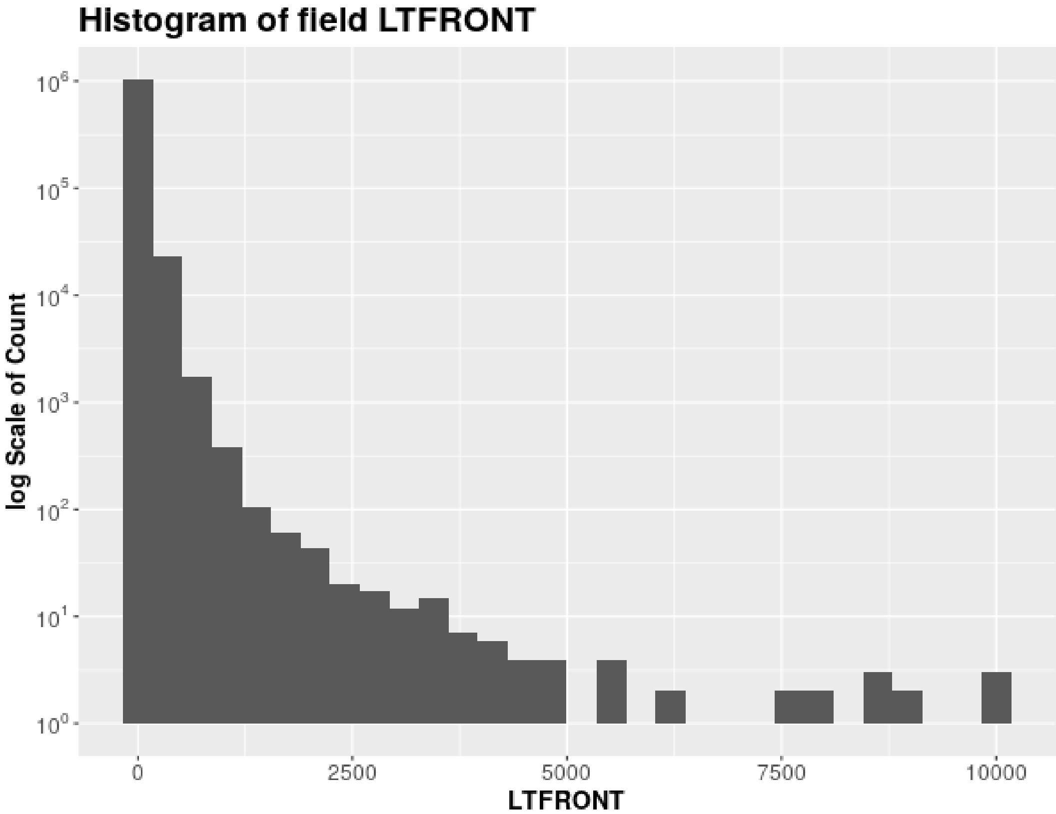
Top10 Field Value Plot



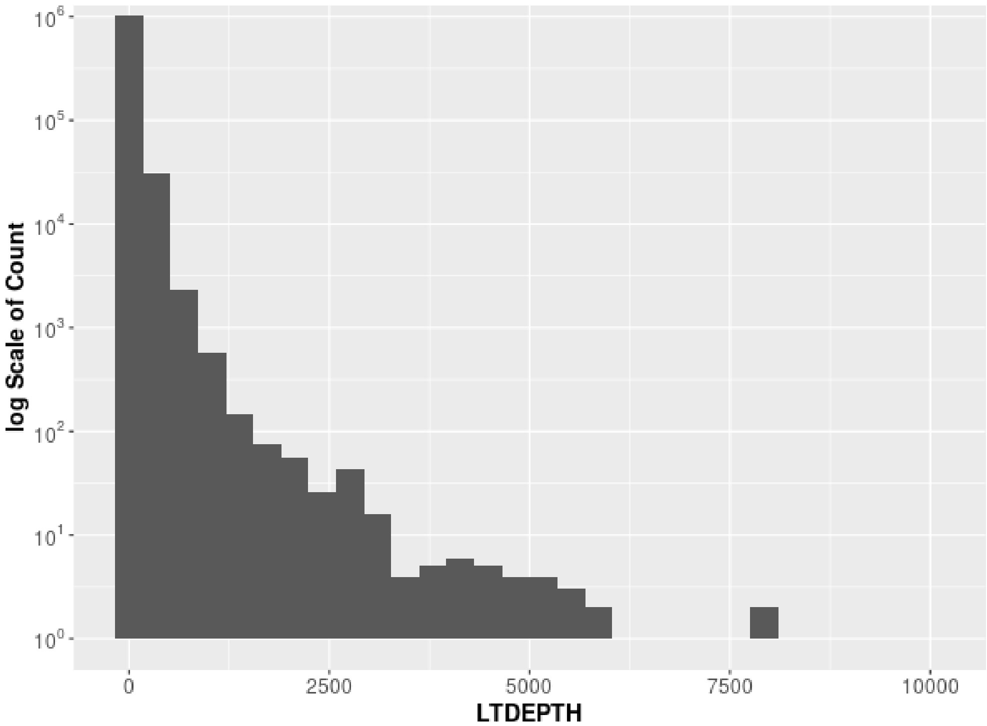
Field 9
Field Name: TAXCLASS
Description: Current Property Tax Class Code (NYS Classification).



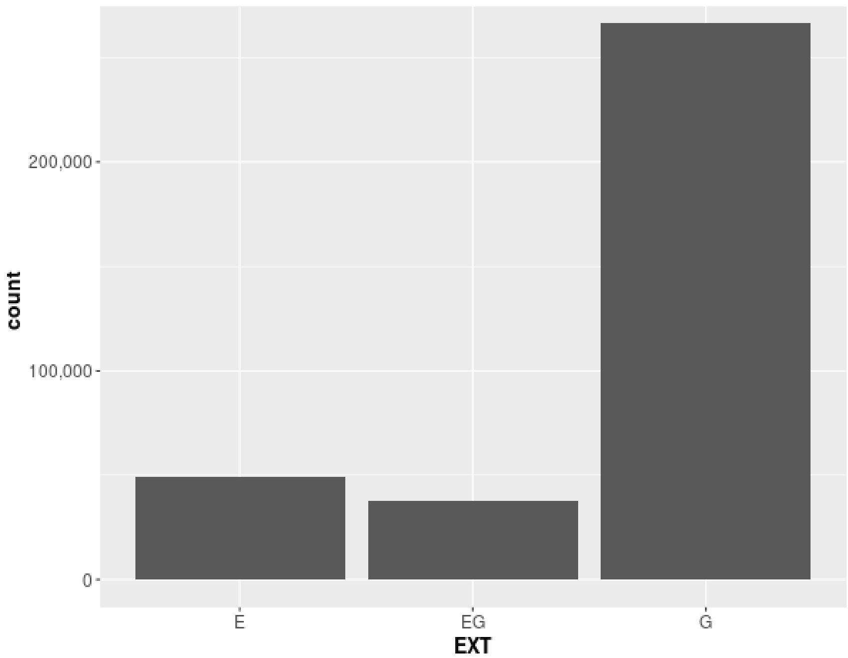
Field 10
Field Name: LTFRONT
Description: Lot Frontage in feet.



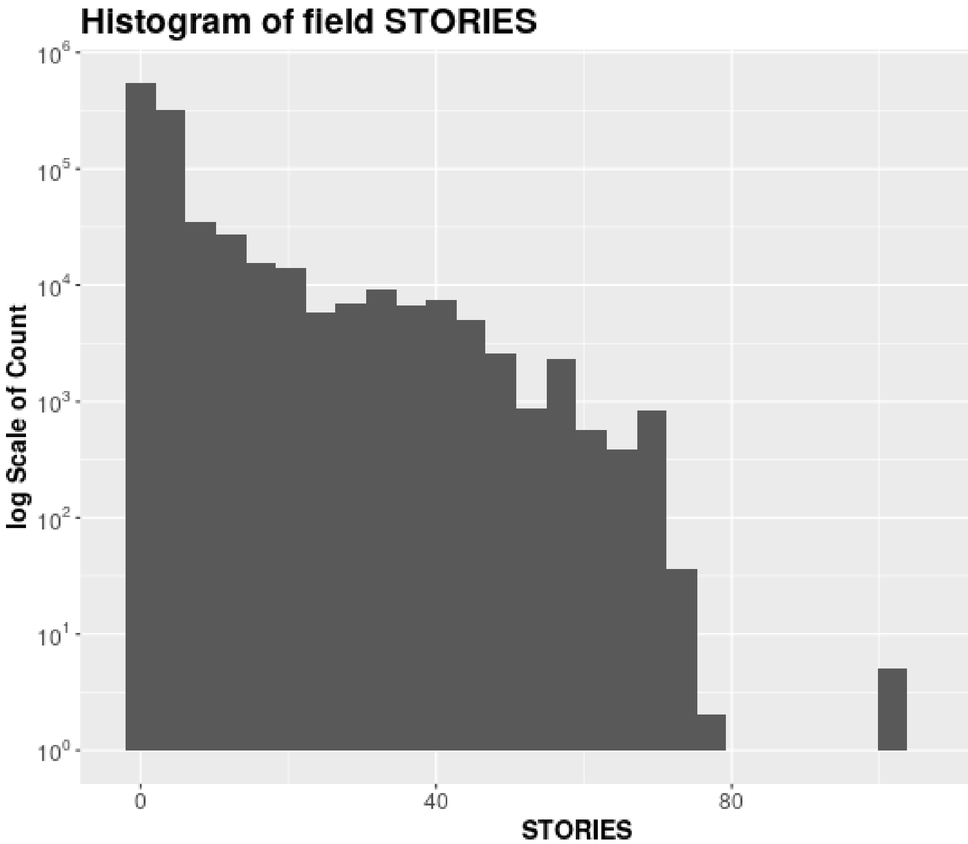
Field 11
Field Name: LTDEPTH
Description: Lot Depth in feet.



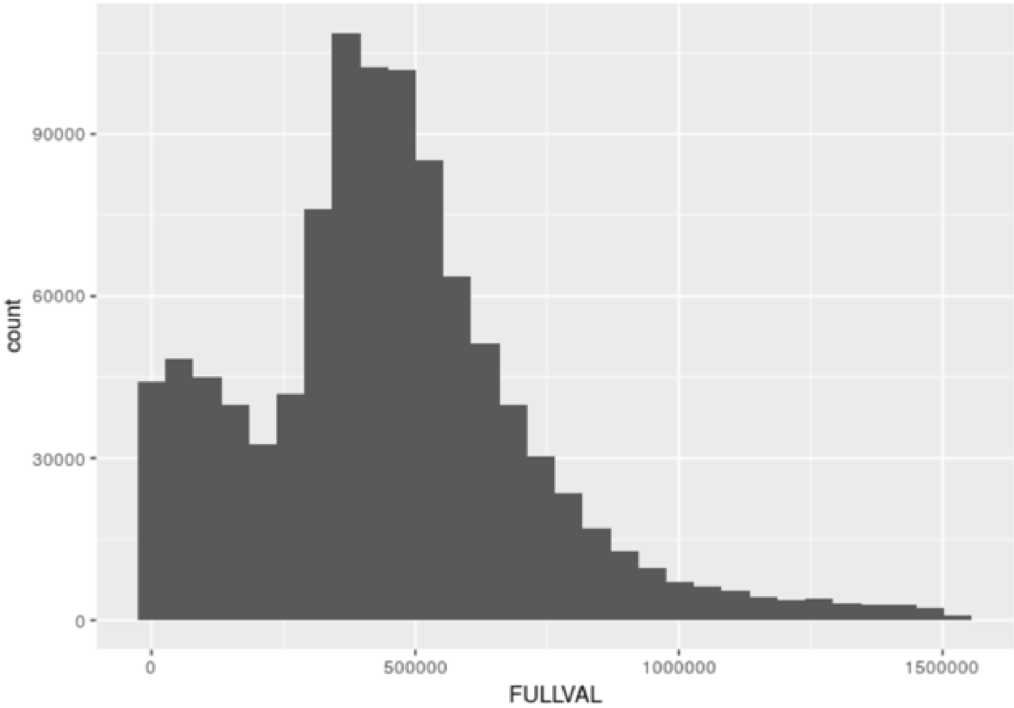
Field 12
Field Name: EXT
Description: Extension indicator, including garage and property extension.



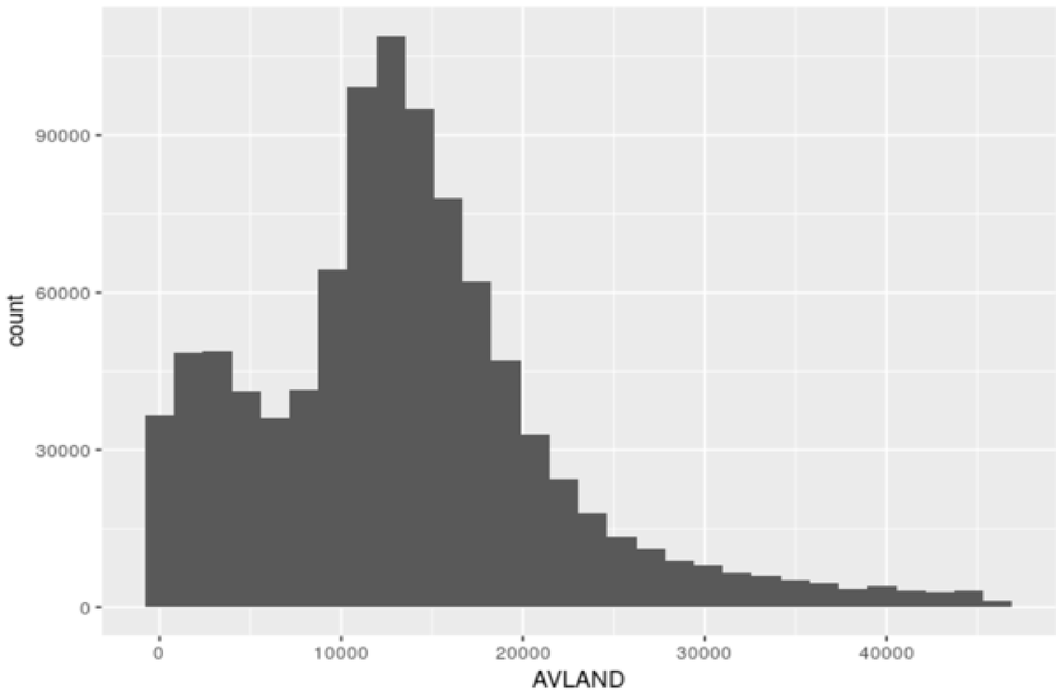
Field 13
Field Name: STORIES
Description: The number of stories for the building (Number of Floors).



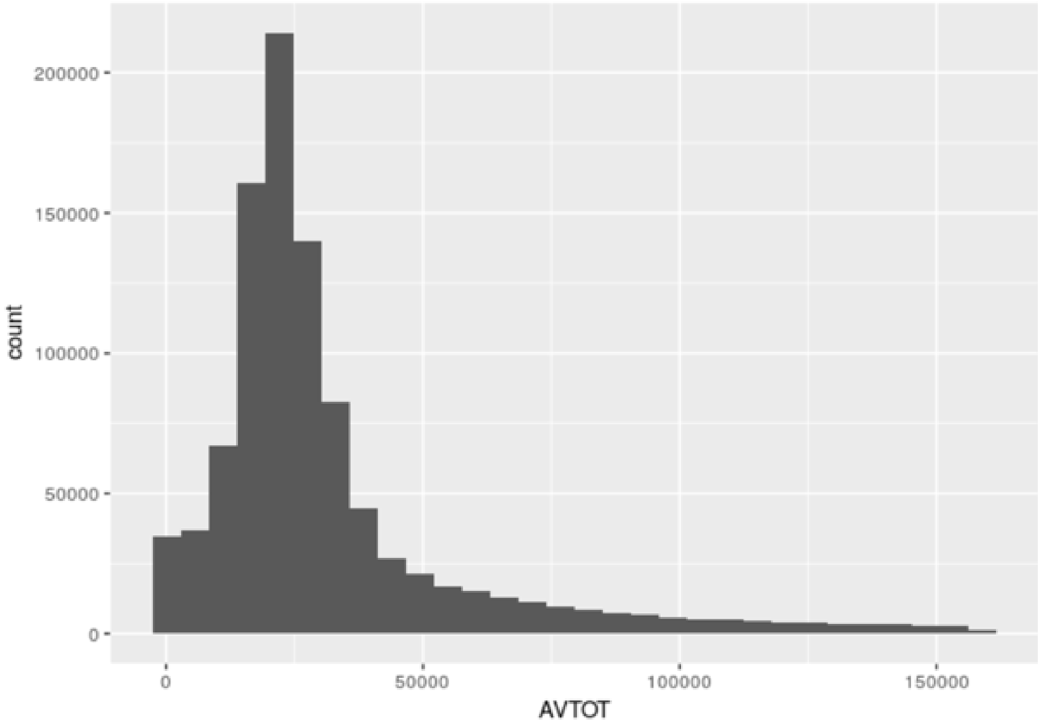
Field 14
Field Name: FULLVAL
Description: If not zero, Current year's total market value of the property.



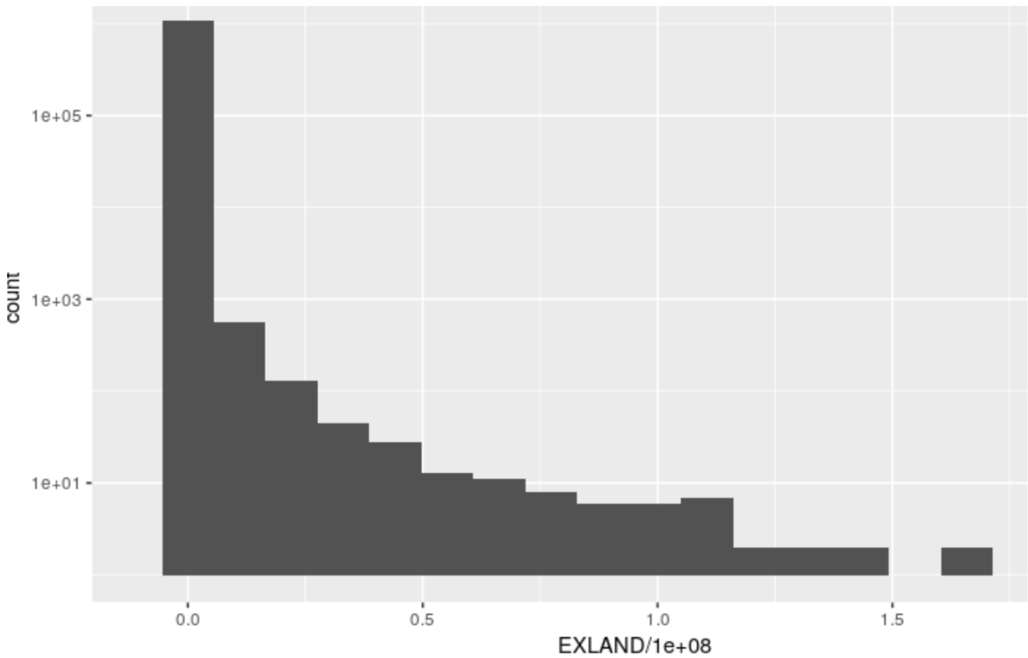
Field 15
Field Name: AVLAND
Description: Assessed land value.



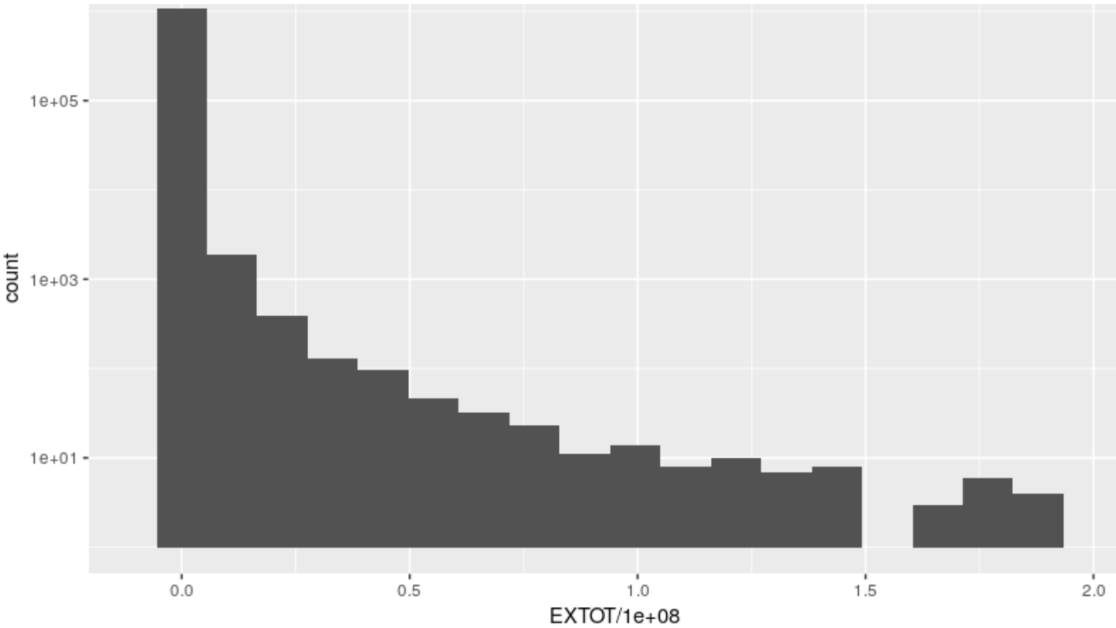
Field 16
Field Name: AVTOT
Description: Assessed total value.



Field 17
Field name: EXLAND
Description: Exempted land value.



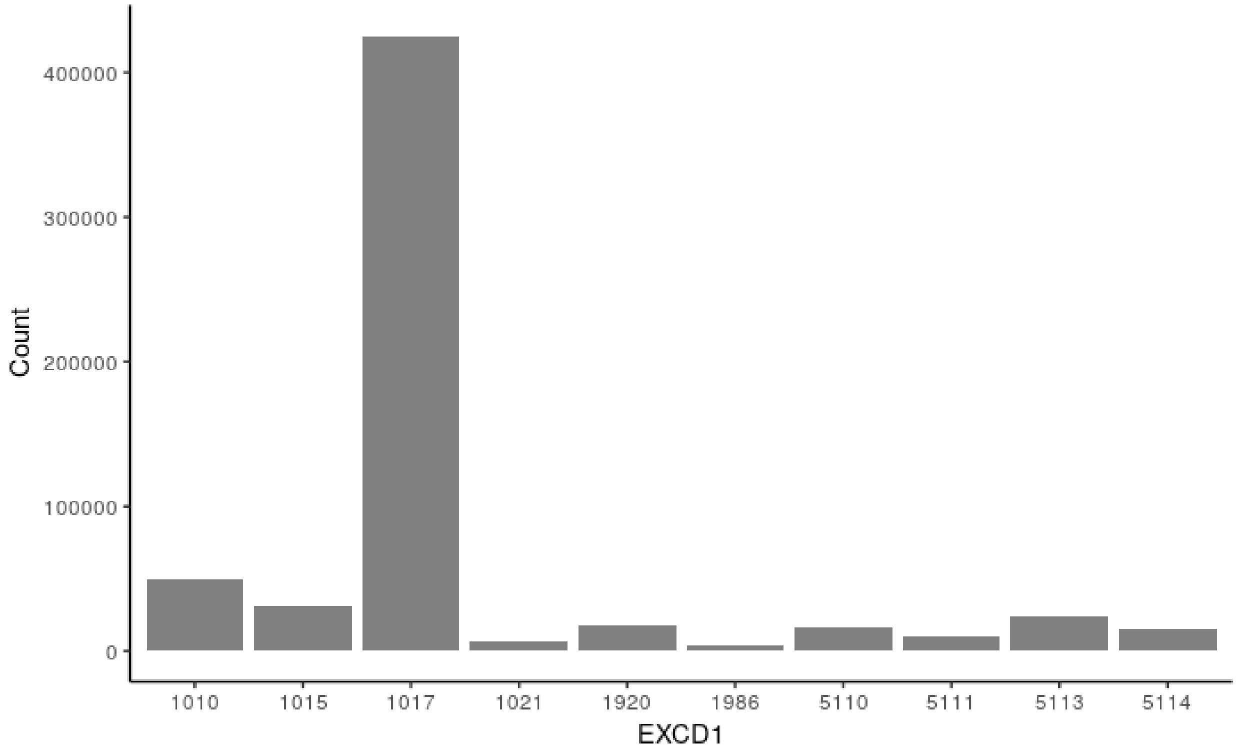
Field 18
Field name: EXTOT
Description: Exempted Total Value



Field 19
Field name: EXCD1
Description: Exempted Current Dollar Value
Top 10 Field Value

	EXCD1	n
1	1017	425348
2	1010	49756
3	1015	31323
4	5113	23858
5	1920	17594
6	5110	16834
7	5114	14984
8	5111	10609
9	1021	6613
10	1986	4231

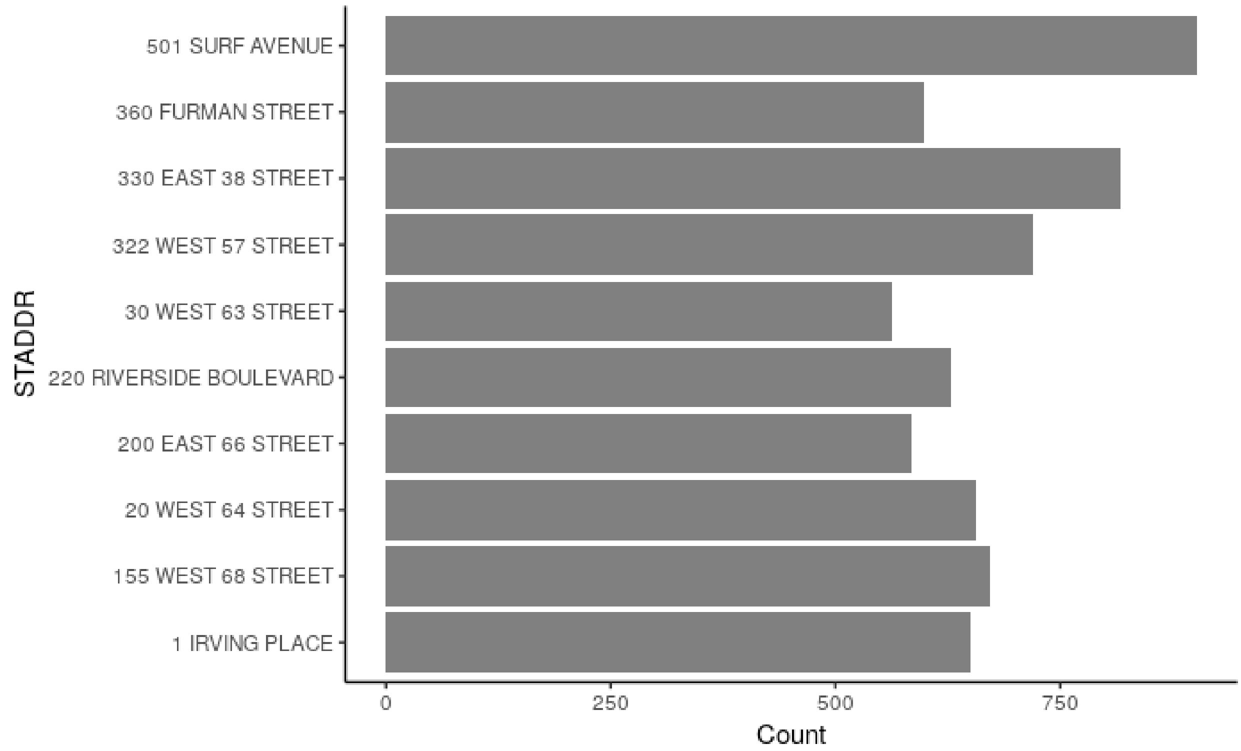
Top 10 Field Value plot



Field 20
Field name: STADDR
Description: Property Street Address
Top 10 Field Value

	STADDR	n
1	501 SURF AVENUE	902
2	330 EAST 38 STREET	817
3	322 WEST 57 STREET	720
4	155 WEST 68 STREET	671
5	20 WEST 64 STREET	657
6	1 IRVING PLACE	650
7	220 RIVERSIDE BOULEVARD	628
8	360 FURMAN STREET	599
9	200 EAST 66 STREET	585
10	30 WEST 63 STREET	562

Top 10 Field Value plot

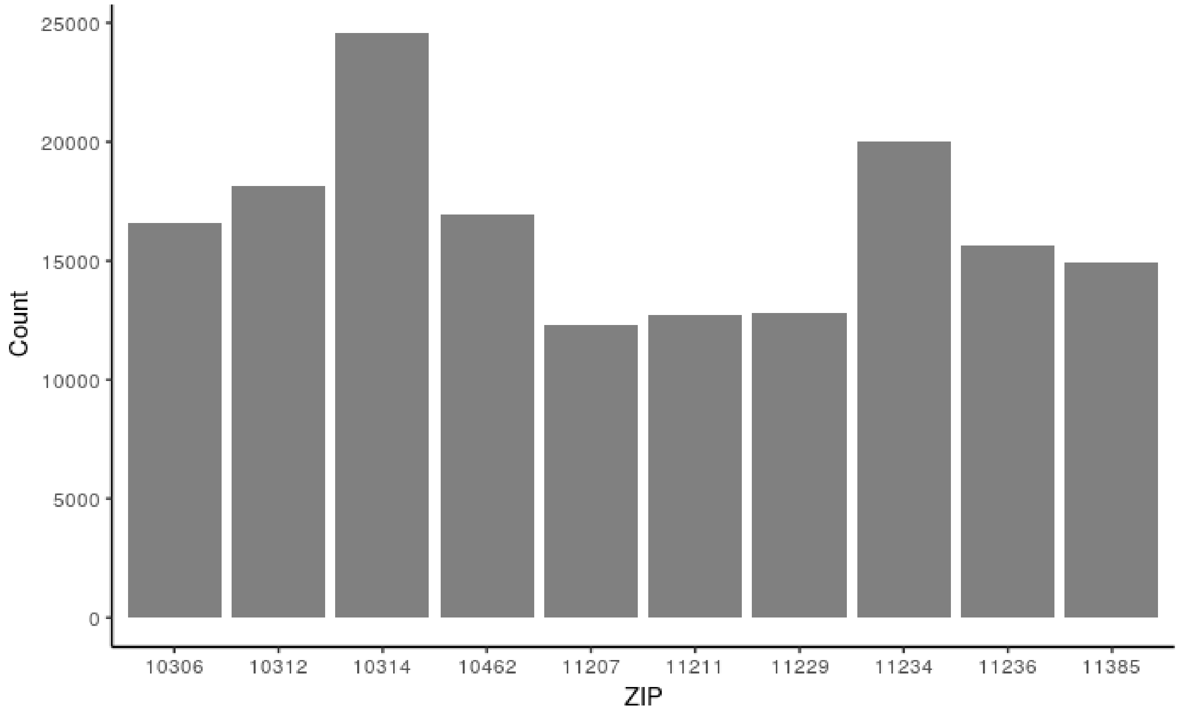


Field 21
Field name: ZIP

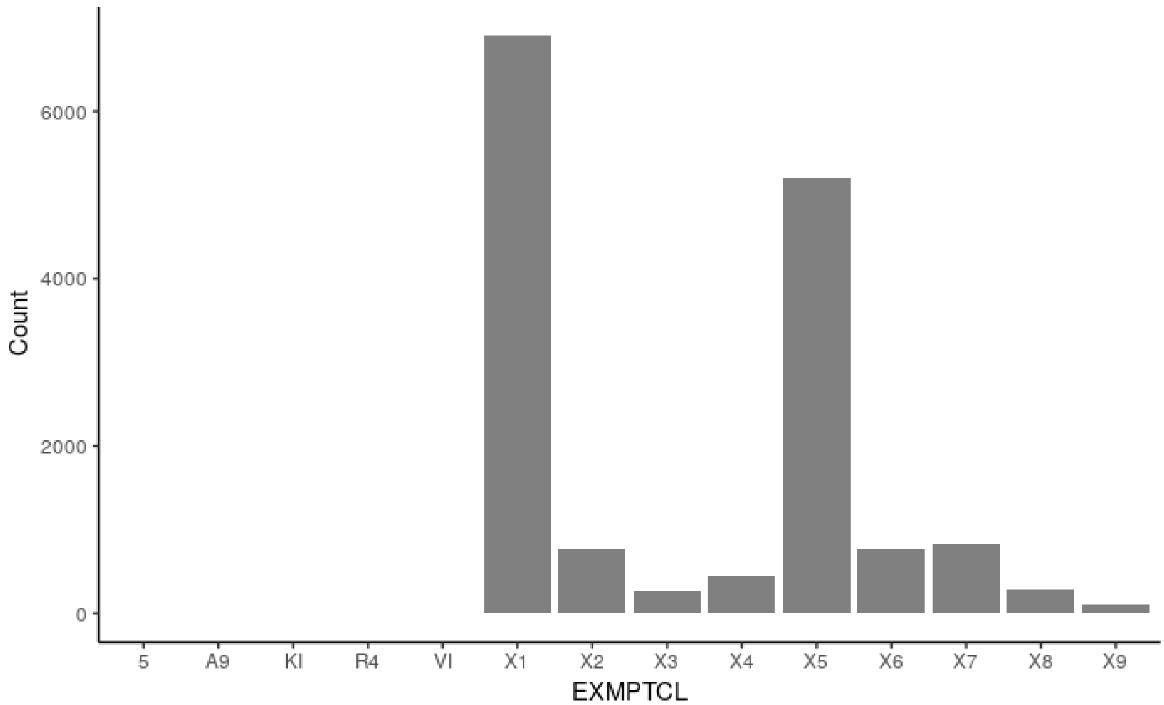
Description: Postal Zip code of the property.
Top 10 Field Value of ZIP Code

	ZIP	n
1	10314	24606
2	11234	20001
3	10312	18127
4	10462	16905
5	10306	16578
6	11236	15678
7	11385	14921
8	11229	12793
9	11211	12710
10	11207	12293

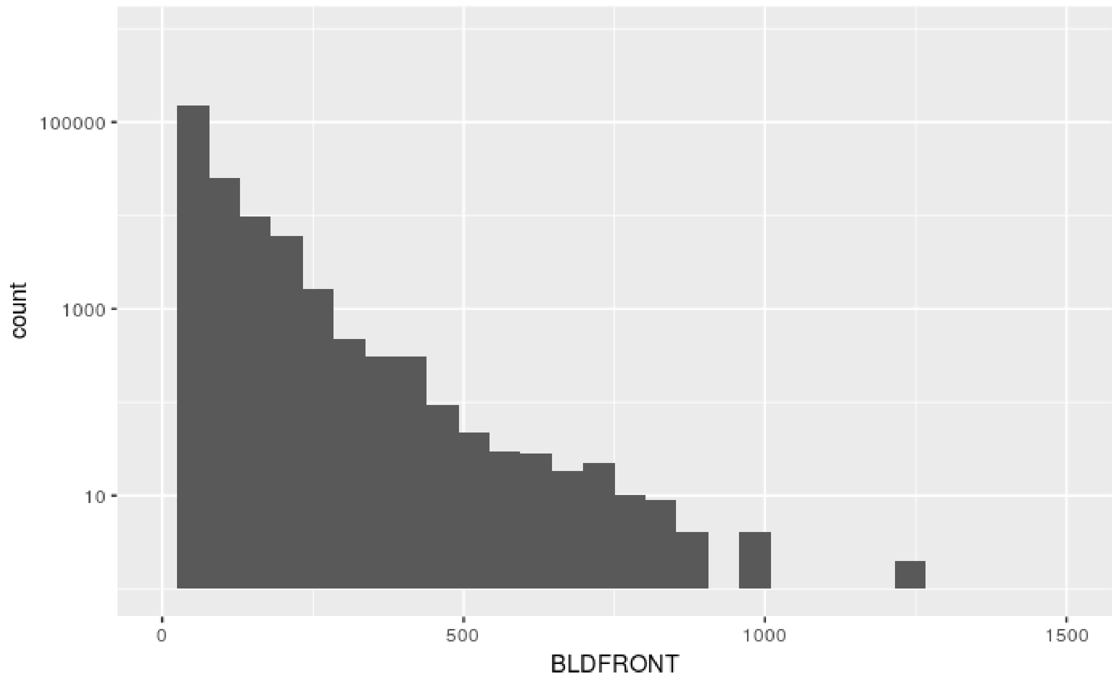
Top 10 Field Value of ZIP Code Plot



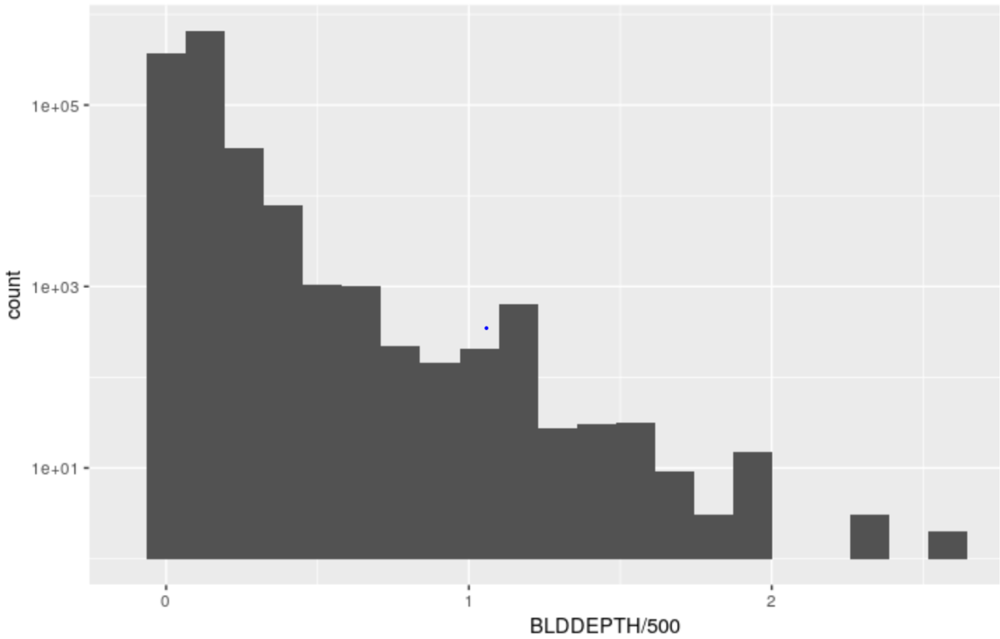
Field 22
Field name: EXMPTCL
Description: Exempt Class used for fully exempt properties only



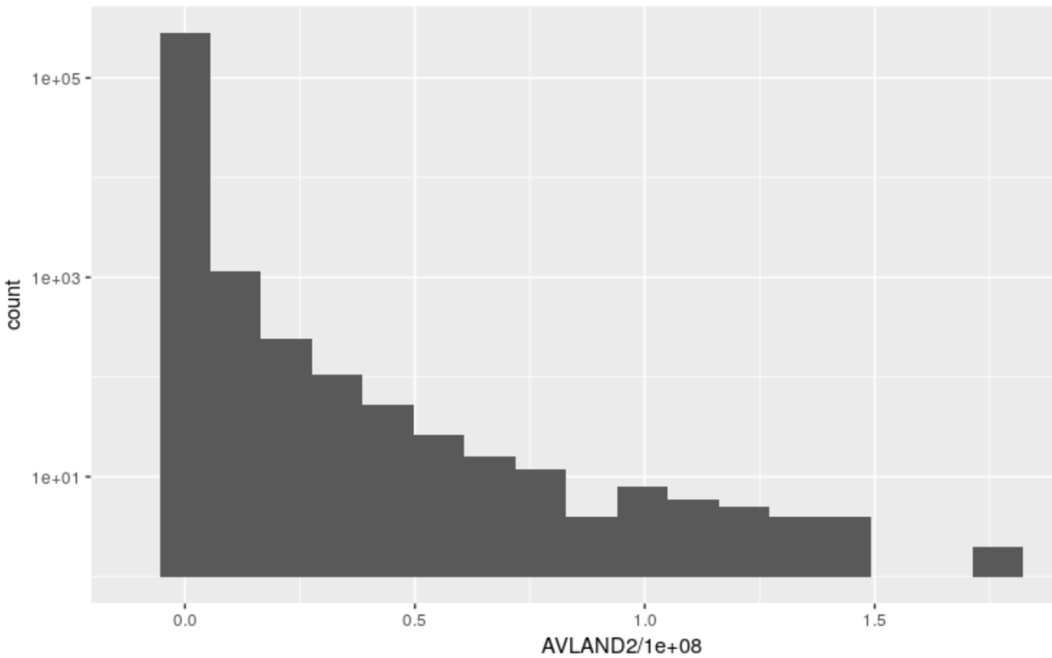
Field 23
Field name: BLDFRONT
Description: Building Frontage in feet.



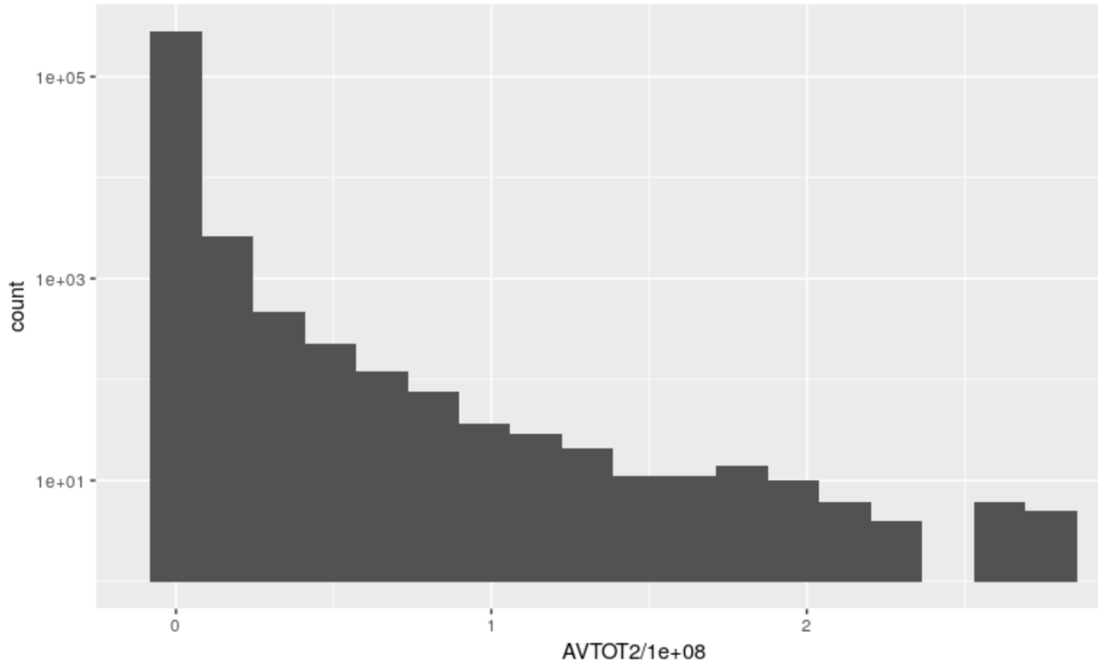
Field 24
Field name: BLDDEPTH
Description: Lot Depth in feet. (With Log Scale)



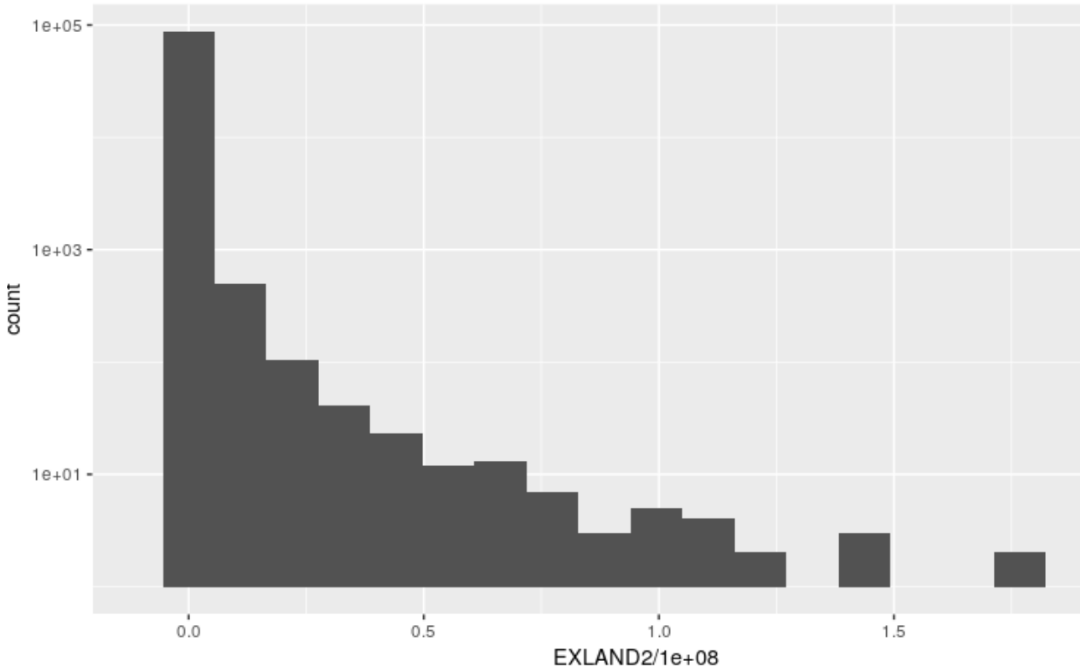
Field 25
Field name: AVLAND2
Description: Averaged Value of Land area (With Log Scale)



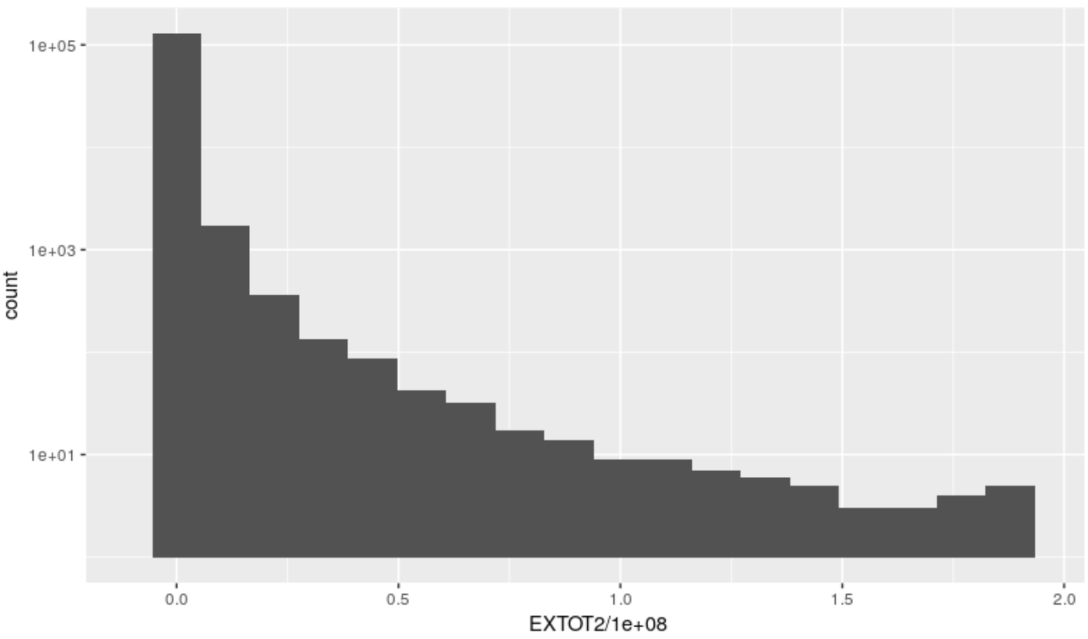
Field 26
Field name: AVTOT2
Description: Total Value area (With Log Scale)



Field 27
Field name: EXLAND2
Description: Exempted Land Value area (With Log Scale)



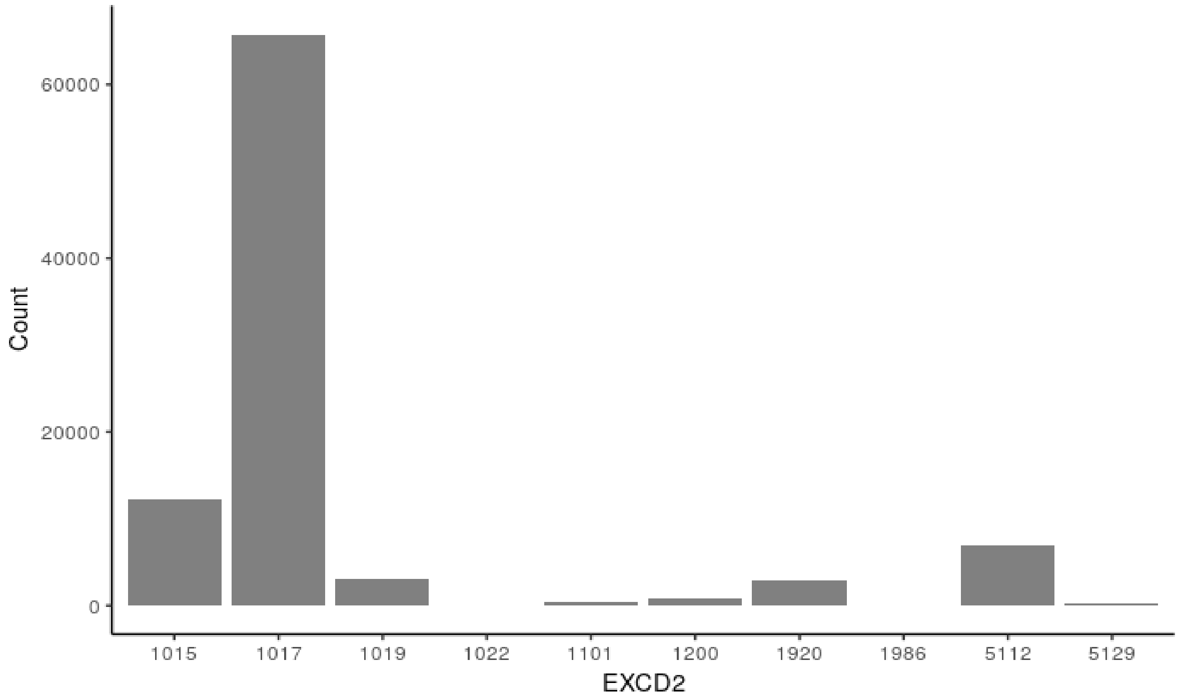
Field 28
Field name: EXTOT2
Description: Exempted Total Value Area (With Scale)



Field 29
Field name: EXCD2
Description: Exempted Current Area
Top 10 Field Value of Exempted Current Area

	EXCD2	n
1	1017	65777
2	1015	12337
3	5112	6867
4	1019	3178
5	1920	2961
6	1200	881
7	1101	494
8	5129	227
9	1986	35
10	1022	31

Top 10 Field Value of Exempted Current area Plot



Field 30
Field name: PERIOD
Description: The Unique Period Value – FINAL Period

Field 31
Field name: YEAR
Description: The Unique Year Value - 2010/11 (The information is in Nov 2010)

Field 32
Field name: VALTYPE
Description: The Unique Value Type is AC-TR

Appendix 2 Top 10 records of Principal Analysis results

RECORD	PC1	PC2	PC3	PC4	PC5
632816	374.63	476.30	-737.94	357.88	45.35
565392	835.68	-130.91	419.64	187.06	-1.30
1067360	153.30	-673.24	-451.05	-159.73	-185.30
917942	205.67	105.14	125.75	-80.38	-584.23
85886	135.50	121.35	-38.03	-340.18	234.35
556609	61.50	-144.65	35.11	130.61	275.04
912501	73.60	-112.86	23.70	38.05	276.93
821853	64.31	-196.77	-17.44	107.63	180.94
776306	53.19	-156.76	2.74	115.51	199.36
770594	32.77	-172.63	-154.26	-94.63	-119.01

RECORD	Max	Min	Sum of PCs	Squared sum of PCs	Euclidean	Rank
632816	476.30	-737.94	1,992.10	1,041,901.30	1,020.74	1
565392	835.68	-130.91	1,574.59	926,592.30	962.60	2
1067360	153.30	-673.24	1,622.62	740,052.75	860.26	3
917942	205.67	-584.23	1,101.18	416,954.36	645.72	4
85886	234.35	-340.18	869.40	205,170.37	452.96	5
556609	275.04	-144.65	646.92	118,646.53	344.45	6
912501	276.93	-112.86	525.14	96,853.35	311.21	7
821853	180.94	-196.77	567.08	87,479.63	295.77	8
776306	199.36	-156.76	527.56	80,497.55	283.72	9
770594	32.77	-172.63	573.29	77,787.19	278.90	10